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Buried-Object-Detection Improvements Incorporating Environmental Phenomenology into Signature Physics

Jay L. Clausen, Vuong Truong, Sophia Bragdon,
Susan Frankenstein, Anna Wagner, Rosa Affleck,
and Christopher Williams

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Abstract

The ability to detect buried objects is critical for the Army. Therefore, this report summarizes the fourth year of an ongoing study to assess environmental phenomenological conditions affecting probability of detection and false alarm rates for buried-object detection using thermal infrared sensors. This study used several different approaches to identify the predominant environmental variables affecting object detection: (1) multilevel statistical modeling, (2) direct image analysis, (3) physics-based thermal modeling, and (4) application of machine learning (ML) techniques. In addition, this study developed an approach using a Canny edge methodology to identify regions of interest potentially harboring a target object. Finally, an ML method was developed to improve automatic target detection and recognition performance by accounting for environmental phenomenological conditions, improving performance by 50% over standard automatic target detection and recognition software.

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Preface

This study was conducted for the US Army Combat Capabilities Development Command, Night Vision and Electronic Sensors Directorate (NVESD), under PE 0602712A, Project H24, “Modernizing Environmental Signature Physics for Target Detection.” The program monitor was Dr. Robert Davis.

The work was performed by the Biogeochemical Sciences Branch (Mr. Nathan Lamie, chief), the Terrestrial and Cryospheric Sciences Branch (Dr. John W. Weatherly, chief), the Engineering Resources Branch (Dr. Melisa Nallar, acting chief), and the Force Projection and Sustainment Branch (Dr. Wade Lein, acting chief) of the Research and Engineering Division, US Army Engineer Research and Development Center, Cold Regions Research and Engineering Laboratory (ERDC-CRREL). At the time of publication, Dr. Caitlin A. Callaghan was division chief, and Dr. Robert Davis was the technical director for Geospatial Research and Engineering/Military Engineering. The acting deputy director of ERDC-CRREL was Mr. Bryan E. Baker, and the director was Dr. Joseph L. Corriveau.

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The commander of ERDC was COL Christian Patterson, and the director was Dr. David W. Pittman.

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1 Introduction

The environmental phenomenological factors affecting the ability to detect surface and subsurface objects with long-wave-infrared (LWIR) thermal sensors are still not well understood. To address this issue, the US Army Engineer Research and Development Center (ERDC) has undertaken a multiyear study (Clausen, Dorvee, et al. 2020; Clausen et al. 2021, 2022; Musty et al. 2022). These studies used the ERDC and US Army Combat Capabilities Development Command C5ISR (Command, Control, Communications, Computers, Cyber, Intelligence, Surveillance, and Reconnaissance) Test Bed constructed at the Cold Regions Research and Engineering Laboratory (CRREL) in Hanover, New Hampshire.

1.1 Phase I

The first study, referred to as Phase I, which was conducted in 2016 to 2018, involved construction of a test plot containing buried objects and sensors emplaced with minimal soil disturbance (Clausen, Dorvee, et al. 2020). The findings showed that significant spatial and thermal temporal variability is caused by varying meteorological and soil-property conditions (Workman and Clausen 2019). On the meteorology side, the key phenomenological factors are the amount of incoming solar radiation and meteorologically driven surface heat exchange. The key soil properties are subsurface-soil temperatures, density, soil moisture content, and surface roughness (Frankenstein et al. 2020). Phase I concluded that the surface-soil temperature is extremely variable and that the amount of temperature variance changes throughout a 24-hour cycle as does the spatial distribution of surface-soil thermal anomalies (Clausen, Musty, et al. 2020). Consequently, comparing two different days with identical environmental conditions for a given time within a 24-hour cycle does not always produce the same spatial background and target thermal response. In addition, plastic objects heat and cool more rapidly than metal objects.

Findings from Phase I also indicate that time differencing of images enhances detection of buried objects as compared to background noise, making it possible to find objects not visible in a single image frame. Time differencing impacts on visibility metrics indicated a normalizing contrast metric was most useful for object detection. The normalized contrast metric showed the soil over buried objects exhibits a larger difference in

derived infrared (IR) temperature than background locations, resulting in better detection of buried objects during sunny and warmer days near solar noon. Deeply buried objects became easily visible when incoming solar radiation was greater than 900 W/m².*

1.2 Phase II

A second study, conducted in 2017 to 2018, referred to as Phase II (Clausen et al. 2021), involved removing soil from the test-plot area, homogenizing the material, then reapplying it into eight discrete layers, or lifts, along with buried sensors and objects representing targets of interest. Following object and sensor placement, each lift was lidar surveyed and then covered with soil previously removed from the test-plot and compacted to a uniform soil density consistent with the background undisturbed conditions. Homogenization of the test-plot soil greatly reduced the microscale surface-soil-temperature variability, simplifying the analysis of the data. The Phase II report (Clausen et al. 2021) focused on the design of the CRREL test plot along with data collection methodology and initial observations. Initial analyses were performed with a cross-correlation statistical technique for determining the potential impact of meteorological factors. In addition, a simple contrast metric for detecting buried-object visibility in thermal IR imagery was utilized.

The Phase II results indicated that, during sunny and warmer days near solar noon, soil over buried objects exhibited a much larger difference in derived thermal IR temperature (thermally visible) than the background undisturbed areas. Consequently, the best time for detecting the buried objects with thermal IR was during sunny days corresponding to high solar loading. Finally, the soil over buried objects exhibited less contrast in thermal IR images during windy days at the test site, implying the objects would be more difficult to identify as wind speed increased.

1.3 Phase III

The research aims of Phase III (Clausen et al. 2022), conducted from 2018 to 2019, and a comparison study with Yuma Proving Ground (YPG) (Musty et al. 2022) was to continue to improve our understanding of the

* For a full list of the spelled-out forms of the units of measure used in this document, please refer to *US Government Publishing Office Style Manual*, 31st ed. (Washington, DC: US Government Publishing Office, 2016), 248–252, <https://www.govinfo.gov/content/pkg/GPO-STYLEMANUAL-2016/pdf/GPO-STYLEMANUAL-2016.pdf>.

environmental (soil and atmospheric) phenomenological properties affecting soil temporal and spatial thermal variance and the ability to detect surface and subsurface objects. The CRREL test-plot configuration used to facilitate this effort was identical to the Phase II setup, described in detail in Clausen et al. (2021).

Phase III (Clausen et al. 2022) was a comprehensive follow-on analysis of the data collected and discussed in the Phase II report (Clausen et al. 2021) using a multipronged analytical approach: (1) multivariate statistical analyses for detecting objects in soil, (2) a moving box analysis of object visibility with alternative methods for converting forward-looking infrared (FLIR) camera radiance values to thermal temperature values, (3) a calibrated thermal model of soil temperature using thermal IR imagery, and (4) a simple classifier method for automating buried-object detection. The study found that a shallow plastic (SP) object was detectable more frequently than a shallow metal (SM) object, and deeper buried objects (deep metal [DM] and deep plastic [DP]) were more difficult to detect. The environmental phenomenological variables affecting soil and object temperature contrasts the most were background surface-soil temperature and soil moisture.

Two methods investigated for converting thermal IR radiance values to thermal temperature values correcting for air temperature, relative humidity, and emissivity yielded similar results. A thermal model was also developed for the test bed, and the calibration yielded reasonably good agreement with actual soil-temperature measurements. In addition, an improved classifier was developed. The classifier generates area under the curve (AUC) values for nine discrete sections of the test plot using raw thermal IR radiance values for thermal IR images both before and after object emplacement. Determining the relative effect of the different variables on object visibility utilized a nonlinear interpretation with Shapely values applied to environmental variables such as solar loading, soil moisture, air temperature, and soil conductivity having the greatest effect, in that order.

The EDRC-CRREL team, along with personnel from the ERDC Geotechnical Structure Laboratory (GSL) and the Desert Research Institute, also performed a field test over an 11-day period at the YPG test site in Yuma, Arizona, during February 2020. This test expanded on CRREL's Phase II (Clausen et al. 2021) findings by gathering data on buried-object visibility

from a secondary location besides the CRREL test plot. Musty et al. (2022) reported the findings from the test effort. In the test, two metal and plastic objects were buried at two depths with the object size, composition, and depths identical to the CRREL Phase II test-plot configuration (Clausen et al. 2021). In addition, the visibility of plastic and metal surface objects was tested using a total of six hockey-puck-shaped objects all painted a uniform desert brown color to visually blend in with the surface soil.

The same FLIR camera used at the CRREL test plot was used at the YPG test site. The thermal imagery collected for the buried objects exhibited a similar behavior for both datasets. In general, object visibility predictably followed solar loading, with times coinciding with the crossover yielding the least visibility. Soil moisture tended to confound this effect, with increased soil moisture typically reducing target visibility. In the YPG dataset, solar loading, soil moisture, air temperature, and soil conductivity were the most impactful environmental variables on object visibility. This finding differs slightly from the CRREL test-plot findings in that air temperature appeared to have an impact on target visibility at CRREL more than at YPG. Variables with little effect on target visibility across both datasets included wind speed, humidity, and atmospheric pressure.

1.4 Phase IV

Two separate activities conducted under Phase IV included (1) development of a three-dimensional heat and mass transfer model for the YPG test bed and (2) efficient generation of artificial intelligence / machine learning (AI/ML) synthetic imagery to train ML algorithms for detecting objects of interest. Both activities will be described under a separate ERDC technical report currently under development with publication anticipated later in FY22.

The first activity involved developing a three-dimensional heat and mass transfer model for the YPG 3.05×3.05 m test bed, which was based on a model developed for the CRREL test site. The YPG model was used to explore the effects of atmospheric conditions and soil properties on the thermal expression of buried objects in an arid desert environment to contrast with the CRREL/C5ISR test bed, which approximates Baltic-like environmental conditions. Additionally, this effort focused on generating synthetic imagery for both the CRREL/C5ISR and YPG sites. This required that the models be run in the context of the Virtual Environment for Sensor Performance Assessment; a modeling suite consisting of vegetation, soils (heat

and mass transfer), a ray caster, and sensor models under development by the Model-Based Assessment of Sensors and Countermeasures research group at ERDC-GSL. The purpose was to compare model-generated synthetic imagery with actual imagery followed by iterative model adjustments to improve performance.

The second activity involved development of an automated integrated framework for creating the input files for multiple runs (approximately 100 simulations) that will eventually be fed to the high-fidelity physics simulator on the ERDC Information Technology Laboratory high-performance computer system. The efficient framework developed will tag the sensor images generated from the high-performance computer simulations appropriately so they can be used for training ML algorithms to improve their performance and aid in a thorough system assessment. Also, an efficient framework is being developed to manage the huge ML datasets for efficient storage and retrieval of real and synthetic sensor imagery.

1.5 Background

1.5.1 Thermal properties of soils

The thermal properties of soil are inherently heterogeneous due to variations in soil characteristics and ambient environmental conditions. The composition of the soil plays a role in the observed thermal response. For example, a sandy soil retains less moisture compared to a loamy soil, and the moisture content of the soil affects the observed thermal signature (Hong et al. 2002). A variety of other environmental factors affect the thermal IR signature of soil: soil moisture and temperature, which are temporal variables; soil density, which is a physical property; surface texture, which is a topological property; and reflectance, a spectral-optical property. It is well known that the thermal response of surface soil is subject to diurnal and annual changes due to daily and seasonal fluctuations in incoming solar radiation (Šimůnek et al. 2001; Hong et al. 2002; Clausen, Musty, et al. 2020).

1.5.1.1 General properties

Beyond the predictable daily and annual cycles in incoming solar radiation, the meteorological and environmental conditions further contribute to variable thermal responses. For instance, Clausen, Dorvee, et al. (2020) compared the surface temperature of a loamy soil on three separate days

(25–27 September 2016) at 1700 hours with the sun angle at 8° above the horizon. For this comparison, the air temperature on each day was approximately the same with similar environmental conditions at the time of observation. The observed weather conditions for the 3 days were (1) sunny all day, (2) morning fog with afternoon sun, and (3) morning fog and rain with afternoon sun, respectively. Despite the similar conditions, the mean and range of the measured surface-soil temperature was vastly different each day, indicating the heterogeneous nature of the thermal-signature response observed in the surface soils. In this comparison, the day with the highest maximum air temperature corresponded with the day with the lowest mean surface-soil temperature. In contrast, the day with morning fog and rain had the second highest maximum air temperature and the maximum mean surface-soil temperature. Prior environmental conditions were like these 3 days, and nothing obvious can be attributed to the difference. These observations indicate that the thermal response of surface soils is a result of a complex interplay of the observed environmental and meteorological conditions and cannot be attributed to one single factor, such as maximum air temperature.

1.5.1.2 Thermal response between buried objects and background soil

The key to detecting buried objects with thermal IR is the ability to identify anomalies in the soil surface temperature caused by the presence of a buried object as compared to background conditions. Thermography is a useful tool for detecting buried objects as it can detect objects of varying material composition during both day and night. Both the composition of the object and the burial depth influence the thermal response observed between the buried object and the background soil (Clausen, Dorvee, et al. 2020). Further, the environmental and meteorological conditions, such as soil moisture content and incoming solar radiation, impact the ability of thermal imaging to detect buried objects (Clausen, Dorvee, et al. 2020, 2021, 2022). In general, visibility of buried objects is higher when incoming solar radiation is high, and the visibility is lower when the incoming solar radiation is low. However, in instances of very high solar irradiance at peak sunlight hours, the prolonged exposure to incoming solar radiation causes a “washout effect” in which the buried objects are masked by thermal equilibrium between the object and surrounding environment (Workman and Clausen 2019). The material of the object also plays a role in the visibility in relation to incoming solar radiation. After sunset, when the surface temperatures are cooling, there is a timeframe in which metal objects are more visible than plastic objects because metal more readily

conduct heat whereas plastic has more thermal inertia. Additionally, the variations in soil moisture content due to precipitation events greatly affects the visibility of buried objects. A sudden rain event will cool the surface soils before the deeper soils; thus, objects buried at a shallow depth will cool quicker, and visibility will become poor. Precipitation in the form of snow masks the thermal variability of the soil surface.

Interestingly, deep objects have a short timeframe after a rain event begins when the visibility is increased since the deep objects will be cooled slower than the surface soils as the rainwater seeps into the subsurface soil (Workman and Clausen 2019). Eventually the increased volumetric water content of the soil will mask all buried objects from detection with thermal IR since the rainwater will induce a thermal equilibrium between the surrounding soil and the buried objects, making detection impossible (Clausen, Dorvee, et al. 2020; Clausen et al. 2021, 2022). Overall, the presence of buried objects disturbs the heat and diffusion parameters of the soil, which enables the detection of buried objects when there is an observed change in the thermal response of the soil above the object compared to the background soil. Changing environmental conditions affect the observed thermal response of the surface soil as well as the buried object itself. The magnitude of the thermal response difference between a buried object and the surrounding soil can either aid or hinder detecting the target with thermal IR. Thus, it is important to consider the environmental conditions when using thermal imaging to detect buried objects.

1.5.2 Thermal IR sensor capabilities and application to object detection

Thermal IR sensors are typically designed as microbolometer detectors, which measure incident LWIR radiation via changes in electrical resistance. This input can be either mechanical, magnetic, chemical, radiant, thermal, or electrical in nature (van Herwaarden 1996). All-natural objects exert IR (Planck 1914), where emittance, as opposed to reflectance, is the quantity measured and is proportional to the fourth power of absolute temperature. This passive capability makes thermal cameras a desired candidate for remote sensing without a need for providing an artificial stimulant; and thermal IR has been applied in various disciplines ranging from civil, medical, security, and humanitarian (Krstelj and Stepanic 2000). For object detection, thermal sensors can be hindered by complex environments and elevated background noise that requires a natural heating source (e.g., solar radiation) to increase the temperature differential of the target from the background. A multitude of tools have been developed

to address this noise issue, such as the inclusion of multimodal sources (Devaguptapu et al. 2019), applying ML (Batchuluun et al. 2021), and treating the characterization as an inverse problem (Thành 2007).

1.5.2.1 Surface objects

Fabricated objects are generally constructed of materials that have thermal properties different from the surrounding environment. This contrast in soil thermal properties, including emissivity characteristics, leads to differences in emitted IR radiation (Georgson et al. 1999), enabling the possibility for object detection. However, exact temperature measurements of objects require internal or external calibration, which is dependent on a multitude of factors (e.g., emissivity, ambient temperature, relative humidity, distance, etc.; Colbert 2006). Use of thermocouples (Martiny et al. 1996) or ray-tracing methods (Elfner et al. 2019) has aided this endeavor. However, additional theoretical and experimental data are necessary to develop accurate numerical simulations to measure the difference in temperature between a surface target and ground surface (Schachne et al. 1998).

Other uses of thermography for surface-characterization purposes have extended into defect detection (Datu et al. 2005), medical imaging (Lahiri et al. 2012), and moisture detection (Grinzato et al. 2011). Thermal IR's nondestructive and passive capabilities are continuing to be applied to new fields.

1.5.2.2 Subsurface objects

Like surface objects, the contrast in material composition between the subsurface target and the surrounding environment affects the emissivity of the surface soil, making detection possible (Boras 2000a). But unlike surface detection, subsurface detection involves the direct disturbance of the ground surface's physical properties and its energy flow (Georgson et al. 1999). Georgson et al. (1999) states that the disturbance in water migration induces changes in the soil's thermal conductivity and heat capacity. However, given enough time, thermal contrast either induced with an artificial stimulant or by solar radiation can be detected (Boras et al. 2000b). Muscio and Corticelli (2004) found deserts or arid regions are the most advantageous for subsurface object detection, whereas thick vegetation is more problematic due to the increased complexity of the background noise.

Additionally, subsurface object detection is more difficult than surface target detection because of an increase in background noise and reduced spatial information, hindering the ability to develop accurate simulations for empirical comparisons (Stepanić et al. 2004). Also, surface targets, such as vehicles, are typically much larger in cross sectional area and mass as compared to buried objects of interest to the military. Some strategies to overcome the background noise include varying the sensor orientation with respect to the soil normal (Stepanić et al. 2004) and data fusion of multiple sensor systems (Shrestha and Wontae 2018). Prior knowledge of the properties of the object can enable the application of the inverse problem (Thành 2007) or finite element modeling (Vavilov 2010) to predict temperature flow and ultimately detection.

1.5.3 Environmental phenomenological impacts on thermal IR sensors

A host of environmental factors can affect the probability of detection and false alarm rate (FAR), such as soil and object material variability, porosity, soil disturbance, moisture migration and evaporation, and terrestrial radiant reflection and emittance. Diurnal thermal fluctuations due to changing solar input throughout the day create thermal contrasts at the soil surface (Khanafar and Vafai 2002). Adding to this complexity is the additional influence of a buried object on both heat and moisture transfer (Pan and Mahrt 1987). Increases in soil moisture and density increase thermal conductivity, requiring specified calibration for in situ soil characterization (Smits et al. 2009). Soil moisture can have a disproportionate effect in certain soils, which in turn can be overshadowed by the impact of soil porosity on thermal conductivity, leading to drastic electromagnetic attenuation (Koh and Wakeley 2009). Understanding the phenomenology along with the magnitude of the interference from environmental parameters helps in quantifying these affects and thus improving current detection algorithms through a process of strategic elimination (Howington et al. 2019).

The trend in using active systems in thermal imagery does present some drawbacks as well. What must be considered are the potential scattering mechanisms that exist in the environment as well as the potential for sensor detection by an adversary when using active systems. When airborne particles are a similar size as the wavelength, scattering efficiency increases and detectability decreases. The particles in fogs, mists, and clouds range from 2 to 20 μm , making them effective LWIR scatterers (Hudson and Hudson 1975). Furthermore, rainfall also affects the physical and

spectral properties of soils by changing the surface particle-size distribution caused by the silt particles separating from larger particles in sand-silt soil mixture (Ballard et al. 2013). Ballard et al. (2013) discovered that the reflectance was most profound in the 8.1–9.2 μm band (thermal band). Ewing et al. (2020) went further in exploring the reflectance increase in the reststrahlen band with an increasing sand-silt ratio. Maximum reflectance occurred with 80% sand. Ballard et al. (2013) also demonstrated that mixed soil gives a reproducible decrease in reflectivity.

Changes in soil temperature further affect the thermal conductivity and diffusivity of sand. For the silica sand samples investigated, Smits et al. (2013) discovered that the thermal conductivity and diffusivity increased most noticeably for soil temperatures greater than 50°C, in agreement with independent empirical models. But surface wetness and thermal inertia hinder the accurate prediction of surface temperatures (Price 1985), leading to complex thermal variability. However, several properties of the soil can be rapidly analyzed with near-IR reflectance spectroscopy, which is the dominant analytical technique used for grain and forage quality assessments (Chang et al. 2001).

Additionally, water molecules are IR active, thus atmospheric transmissions in the thermal IR band is degraded by molecular rotational transitions from water vapor or by broadening effects from hydrogen-bonding interactions in the cases of liquid water (Gorman 1957; Raqueno et al. 2008). Van Dam et al. (2003) concluded that water content does indeed affect thermal signatures, though the correlation did not have a quantifiable linear relationship. Instead, accounting for the properties of disturbed and undisturbed soil can help better detect buried objects (Koenig et al. 2008). The presence of a buried object disturbs the heat and diffusion parameters of the soil, enabling anomaly detection (Frost 2006). However, it the research community now generally believes that it is the disturbance of the soil and alteration of the soil properties that gives rise to the thermal signature. Thermal contrasts manifest as a result of three effects: (1) the object itself likely has different thermal properties than the soil it has replaced, which may result in differential heat transport and a thermal expression at the surface; (2) disturbing a soil normally changes its density and thermal properties, also leading to a surface expression of physical temperature; and (3) disturbing a soil redistributes finer particles to the ground surface, which, for some soil compositions, changes their spectral reflectance (S. E. Howington, GSL, pers. comm., February 2020).

Interestingly, the surface effect remains for months after the disturbance and enhances the contrast induced by the buried object, a phenomenon also observed in our earlier work (Clausen, Musty, et al. 2020, 2021).

Swiderski et al. (2012) extended the work of Hong et al. (2002) and van Dam et al. (2003). They used physical measurements and numerical modeling techniques to observe the effects various moisture levels and the density of soil have on buried-object detection. Howington et al. (2012) believed hydrogeological variability must be considered on the same scale as a sensor's image pixels (a few centimeters) to isolate and quantify the near-surface process interactions to produce an accurate simulation. High-resolution synthetic thermal-image production has helped in optimizing explosive detection (Peters et al. 2007). This, combined with mathematical and statistical modelling of the heat and water flow in the soil (Lamorski et al. 2002) is highly dependent on the knowledge of the external conditions. Predicting expected surface-soil temperatures is complicated by the non-linear movement of water within soil and changes in surface temperature during the drying process (Frost 2006). Thành et al. (2011) introduced the inverse problem setting and used a least-squares minimization approach for buried-object detection. Their group confirmed that the deeper the object is buried, the less accurate the reconstruction will be, while larger objects produced greater accuracy upon reconstruction. Their model did not tackle inhomogeneous soil and complex shapes.

Understanding the relationship between meteorological conditions and soil properties is paramount to detect objects buried in soil and to predict sensor performance. An analytical solution requires extensive knowledge of the buried material, the surface composition, the water content, and the humidity of the environment. This multivariate and multilayered problem is thus limited without quantifying the environment absolutely. Van Dam (2003) stated that without knowing all the parameters involved, it is impossible to predict the thermal signatures accurately.

1.5.4 Multisensor fusion including thermal IR

However, the sensor application community has been exploring “active” ways to increase probability of detection of buried objects by utilizing a multisensor approach, sometimes referred to as sensor fusion. Recently, studies have shown the resolution and contrast of thermal imaging to improve significantly by utilizing polarized thermal sensors, which have the potential to simultaneously decrease background clutter while increasing

contrast and producing highly resolved fused images (Baur et al. 2018; Jarrod et al. 2019). Disturbed regions in comparison to the surrounding exhibit higher degrees of linear polarimetric contrast (Gurton and Felton 2012). Gurton and Felton (2012) utilized a spinning-achromatic-retarder platform for LWIR polarimetric imaging, resulting in improved detectability regardless of the geographic location or soil type. Similarly, Abbott et al. (2020) created an effective detection algorithm by utilizing RGB imagery for translating noncorresponding LWIR/RGB datasets due to the lack of standalone IR annotated data. Pinar et al. (2017) added in a forward-looking ground-penetrating radar (GPR) and lidar in unison with their visible and thermal camera, improving the signal-to-noise ratio (SNR) and thus increasing classification accuracy of the buried target.

Active systems, such as GPR coupled to a thermal camera's superior stand-off capabilities, complement GPR's higher detection performance (Malof and Collins 2016; Hendrickx et al. 2006). As a standalone sensor modality, GPR has been gaining popularity in subsurface object detection (Shaw et al. 2016; Kelly et al. 2019). Studies have extensively explored the polarization effects on GPR (Dogaru and Le 2016; Sagnard 2017) and the effects from soil moisture (Miller et al. 2002, 2004). The Miller et al. (2004) field measurements concluded that increasing soil moisture around a nonmetallic buried object can improve detection in sand and silt soils due to the increasing contrast in the soil's bulk dielectric constant as the water content increases. Clay soils on the other hand showed the opposite effect, with greater attenuation with increasing water content, limiting GPR's potential as a standalone sensor modality.

Other techniques in buried-object detection include the use of microwave generators (Deans et al. 2001) and IR heaters (Yao, Wen, and Wang 2019), which are utilized simultaneously with a passive thermal sensor to complement and stimulate thermal variability. Yao's team used an IR lamp adjusted to 800 W/m^2 to mimic the natural diurnal cycle of Earth in a controlled indoor environment. Li et al. (2020) took a different approach by observing how buried objects impacted the acoustic-to-seismic coupling efficiency by tracking the changes in acoustic impedance. Similarly, von Deimling et al. (2015) utilized a parametric echosounder system to investigate the angular response of the backscatter on underwater targets. Finally, Kabessa et al. (2016) introduced a standoff biosensor capable of buried-object detection.

1.5.5 Automatic target-recognition software applications for thermal IR

The military uses thermal IR paired with automatic target detection and recognition (AiTD/R) software to detect an object within a scene. For example, a common application is to detect vehicles aerially with FLIR cameras since a vehicle will have a different heat signature than the surrounding scene. The path of a moving vehicle will also leave a heat signature on the soil surface due to disturbance of the soil that differs from the background scene. Other applications include detection of helicopters, ships at sea, and people (Bhanu 1986; Bhanu and Jones 1993; Nasrabadi 2019; Schachter 2020; McIntosh et al. 2020). Thermal imaging coupled with AiTD/R software is also used to detect targets both above and below ground (Nguyen et al. 2005; Hong et al. 2002; Šimůnek et al. 2001). All applications of AiTD/R software must perform two key tasks: the detection of an object from the background scene and the subsequent classification of the object.

For the detection step of AiTD/R algorithms, the user must identify a region of interest (ROI) in the image, and the second classification step of the algorithm determines whether the ROI is indeed an object or background clutter. The more cluttered the scene, the more difficult it is to identify ROIs that contain objects of interest. In the context of a buried object, the thermal signature varies widely throughout the day; and at times with a low SNR, the detection step of an AiTD/R algorithm is challenging. A simple approach to the detection step is called the double or triple window filter (Schachter 2013, 2020). To perform this detection algorithm, one computes a t-test statistic where one sample is selected from the inner window and compared to a sample selected from the outer window. If the statistics of the inner window vary greatly from the outer window, then the t-test statistic will return a larger value. Regions of a FLIR image that have a large t-test statistic can be selected as an ROI to be processed in the second classification step of the AiTD/R algorithm. There also exists more sophisticated approaches to identifying ROIs within an image, such as the use of deep neural networks and bounding boxes to identify anomalous regions within a thermal image (Nasrabadi et al. 2018; Nasrabadi 2019). For buried-object detection with FLIR imagery, an edge detection type kernel with a convolutional neural network may be applicable since there are times in the day when the thermal signature of the buried object and that of the background significantly differ.

The classification step of AiTD/R algorithms is commonly performed using a statistical or ML approach. The simplest approach is a two-class classifier in which the ROI is classified as either a target or background noise. For example, a support vector machine can be used to learn the separation between two classes in the case of linearly separable training data. However, not all data can be separated into two classes linearly via a hyper-plane, and a nonlinear or statistical approach may be required. Neural networks such as a short-term memory, region-based convolutional neural network (R-CNN) or a convolutional neural network (CNN) are commonly used for classification into two or more classes. This is done since the neural-network architecture of these algorithms can learn a nonlinear relationship between different classes (Schachter 2015, 2020; Nasrabadi 2019; McIntosh et al. 2020). There is also a class of ML-based automatic target recognition (ATR) algorithms that are one-step algorithms rather than the two-step algorithms described above. These one step-algorithms simultaneously detect and classify ROIs all within a single algorithm rather than coupling two algorithms together to form an ATR. The state-of-the-art one-step algorithms are You Only Look Once (Redmon and Farhadi 2017) and Single Shot Detector (Liu et al. 2016).

1.6 Objective

The objective of this study was to identify the environmental phenomenological variables contributing to either the enhancement or degradation of the ability to detect buried objects. Once identified, the secondary objective was to develop techniques to improve the performance of existing AiTD/R software used by the military.

1.7 Approach

This project comprises a multitude of tasks, including (1) developing an AI/ML image analysis methodology that uses edge detection techniques to improve object detection, (2) quantifying the environmental phenomenology by strategic test-plot manipulations, (3) assessing seasonal impacts on soil thermal response, (4) establishing a relationship between incoming solar radiation and surface-soil temperature, (5) generating heat flow models simulating buried-object-induced soil disturbance that include a physics-based three-dimensional model for the YPG test site, and (6) developing synthetic imagery and an automated integrated framework for their management.

2 Multilevel Modeling

The effects of various surface characteristics, different subsurface-soil properties, and a host of environmental factors influence buried-object detection. The manifestation of the variability within these factors and their interactions with the different soil properties are still poorly understood. For instance, diurnal thermal fluctuations due to changing solar input throughout the day give rise to thermal contrasts at the soil surface, but the relationship between solar input and surface-soil temperature contributing to these contrasts remains undefined. The relationships between thermal response, radiation, and surface-soil temperatures for undisturbed (without buried objects) and disturbed (with buried objects) soil have not been fully examined. However, last year, Clausen et al. (2022) made progress assessing the environmental parameters responsible for the thermal response differences between disturbed and undisturbed areas.

Clausen et al. (2022) analyzed, using multilevel modeling, the relational association between atmospheric energy input and soil response under summer conditions by using data from 15 July to 31 August 2018. For the first part of the analysis, the team examined covariates (atmospheric condition and near-surface-soil temperatures) for the probability of detecting the contrast between the presence and absence of a buried object by using unclustered structures. The distinction between disturbed and undisturbed areas has statistical significance and is statistically related to hourly average surface-soil temperature, subsurface-soil temperature (at 5 cm below ground surface [bgs]), and soil moisture (at 15 cm bgs). In other words, buried objects impact the surface and near-surface-soil temperature as well as soil moisture. Plastic objects retain heat better than metal objects and the surrounding soil while metal objects conduct heat better than plastic objects and the surrounding soil. Both the plastic and metal objects are impermeable, which results in condensation of soil moisture and pooling of precipitation following a rain event above the objects. The work of Clausen et al. (2022) established that the thermal response to distinguish the relationship between disturbed and undisturbed is not directly related to relative humidity (Rh), wind speed, and shortwave reflectance at the CRREL test plot. In the following discussion, the term *contrasts* is used to express the statistically significant surface-soil thermal difference between disturbed and undisturbed areas.

The second part of the Clausen et al. (2022) analysis incorporated the randomness and nonlinearity of outcomes by using nested structures examining (1) which covariates can detect the contrast between disturbed and undisturbed soil; (2) the overall probability of detecting the contrasts, or which contrasts are significant; and (3) the time of day that has the highest unit change (probability) for estimating the contrasts or what is the suitable time for best detection of buried objects in the ground. Overall, the surface- and subsurface-soil temperatures at 5 cm bgs derived with thermal IR provides the best input measurements for detecting the thermal contrast of the buried objects within sinusoidal daily surface-soil-temperature patterns. The sinusoidal surface-soil-temperature patterns reflect diurnal changes due to weather, incoming solar radiation, and evapotranspiration processes. From 1300 to 1345 daily, the soil temperatures at the ground surface above the SP object was approximately 4°C higher than the SM object. The multilevel modeling approach was able to quantify the impact of having buried objects versus no buried objects on shallow surface-soil temperatures. The soil moisture, the measured near-surface-soil temperature, and the measurements for the surface-soil-temperature response derived from thermal IR all affect the contrasts between having buried objects versus no buried objects, particularly for the SP and SM objects.

However, there are specific questions not yet addressed:

1. What is the difference in temperature of the surface soil above an object (by type of material) as a function of the amount of incoming solar radiation? Specifically, how variable is the surface-temperature response above a buried object compared to the background? Alternatively, does the soil temperature of the background area have more temperature variability than above a buried object?
2. What is the thermal contrast in background noise (i.e., spatial surface-soil-temperature variance) as a function of incoming solar radiation? Specifically, what time of day has the most and least background noise as expressed by spatial soil-temperature variance?
3. What causes the spatial variability or the noise in surface-soil temperature as seen in the IR-derived thermal imagery? Why do we see clusters of pixels that are hotter than other areas or vice versa? Specifically, are the hotter and cooler areas associated with specific ground-surface features?

The spatial variability and the noise that are observed in the thermal IR data are thought to be influenced by the surface characteristics of the soil.

This section of the report assesses the impact of surface characteristics on thermal IR as a function of topography, slope, aspect, and roughness.

2.1 Methods

We integrated the lidar data with thermal IR imagery to assess the influence of the surface characteristics of each pixel to quantify the questions above. Once the surface characteristics of each pixel were assimilated with thermal IR temperature data, we used advanced statistical correlation analysis and multilevel modeling to quantify the relationships.

The analysis in this section used the following statistical approaches using the JMP statistical software (version 11), SAS Institute, Cary, North Carolina:

- We used one-way analysis of variance (ANOVA) to analyze the overall hourly mean temperature distribution, the variance, and spatial distribution patterns for the 15 July to 31 August 2018 dataset. This was a simplistic approach to quantify the surface-soil-temperature noise.
- This analysis used the fit model (i.e., multiple linear regression) in JMP (version 11) to examine the correlations based on the standard least-squares method to estimate the best-fitting line of the model coefficient values for the observed data. This aided in analyzing the influence of the ground-surface irregularities, such as topography and surface patterns, on the surface-temperature variation when the ground was warm and dry for the selected 11 rain-free days. The selected period included relatively low- and high-humidity days as well as varying shortwave reflectivity conditions. The regression outcome of the dependent variable, y , in this case soil temperature, is derived from the thermal IR image. The regression is a function of the independent variable x , which is a linear function that produces the best prediction of y . The independent variables included aspect, elevation, and slope. The model is individually grouped by object and background location and separated by date and time. The simple linear regression model is

$$y = \beta_a + \beta_b x, \quad (1)$$

where

β_a and β_b = the intercept and slope of the model, respectively, where β_a is the associated temperature at minimum elevation and associated aspect, and
 x = the independent variable representing the elevation or aspect.

The slope represents the temperature change from minimum to maximum elevation within each test plot. Positive slope values indicate a rise in temperature with increasing elevation, while a negative slope denotes a decrease in temperature with the rise in elevation.

The estimated least-squares regression produced the summary of fit, analysis of variance, effect tests, and scaled-parameter estimates for the variables. The scaled-parameter estimates on the effect screening provide coefficients corresponding to factors that are nominal or categorical that are scaled to have a mean of zero and a range of two. A factor with symmetrically distributed data will have a scale factor ranging from -1 to 1 . The scaled coefficient reported is the temperature change from one aspect category to another and identifies which aspect direction has statistical significance. With emphasis on effect screening, the response of the predictor variables is reported in the model using the Prediction Profiler in JMP to display the predicted outcome at specified values of elevation and aspect. The Prediction Profiler displays the trace of the predicted response along with 95% confidence intervals as one variable (either the elevation or aspect) is changed while the others are held constant at that current value. The summary-of-fit model is evaluated with the associated correlation coefficient, R^2 , and the statistical significance (p). The correlation coefficient, R^2 , is a statistical measure for goodness of fit or how close the data are to the fitted regression line with a value of 1 indicating a perfect fit.

2.2 Data processing

We characterized the surface topography by using lidar data collected with a 5 mm vertical resolution at the CRREL test plot to derive the digital elevation data. The data was processed in a geotiff format with a projection using Universal Transverse Mercator, North American Datum of 1983 coordinate system, Zone 18. The lidar data (in meters) was resampled to produce a 2.7926×2.7926 cm horizontal-resolution lidar image (Figure 1). The resampling was performed to approximately match the 2.90×2.65 cm horizontal resolution of the thermal IR data. Slope and aspect

were generated from lidar elevation data by using ArcToolbox in the 3D Analyst function in ARCGIS Pro (version 10.6, Esri, Redlands, California). The slope is the gradient or steepness from each cell of a raster, in this case the inclination of slope values of each raster (or cell) in degrees. The aspect identifies orientation of slope or the compass direction that the downhill slope faces for each location. The aspect class is populated according to direction categories (Table 1).

Nine bounding boxes consisting of 10×10 pixels, which is the dimension of the buried objects (i.e., 25×25 cm), overlaid the buried objects and background locations (Figure 1). The 10×10 pixels bounding box are within the dimensions of the buried objects, and the analysis was made with respect to pixel size. The center coordinates of each bounding box were determined for the elevation dataset, and these coordinates are the same for slope and aspect datasets. The lidar image coordinates were then mapped to the coordinates of the thermal IR data (Clausen et al. 2021). Because of the resolution differences between the thermal IR images and the resampled lidar elevation data, the corresponding cells do not exactly match each other. Consequently, the average values of the elevation, slope, and aspect were obtained for each cell within the bounding box and related to the thermal IR imagery data. This step allowed for merging the corresponding lidar-derived surface topographic characteristics (elevation, slope, and aspect) with the thermal IR surface-soil temperatures for each bounding box in the test plot, as shown in Figure 1. This means that each bounding box is represented by 100 cells of data distributed in a 29×26.5 cm area.

The data used in the analysis in this section is from 15 July to 31 August 2018 using similar methods to those described in the Phase III report (Clausen et al. 2022). The dataset included the four buried objects (SP, DP, SM, and DP) and five bounding boxes for background locations without buried objects (Figure 1). Since the data were collected every 15 minutes, the time of the day is aggregated from 1 (midnight) to 24 (midnight). A code for time 1 signified an hourly mean of variables for 1200 to 1245, code of 2 for 0100 to 0145, and so on. Thus, the dataset for each bounding box consisted of aggregated hourly mean results for soil surface temperature, air temperature, relative humidity, shortwave incoming radiation, and upwelling shortwave radiation.

Tables 2 to 4 summarize descriptive statistics for elevation, aspect, and slope used in the analyses. Appendix A provides the distribution frequency graphs. Overall, the SM and SP bounding boxes have the most elevation change (i.e., 1.24 and 1.16 cm, respectively, within their 29×26.5 cm area). The topography data has a 2.7926×2.7926 cm spatial resolution with a 5 mm vertical resolution. The maximum vertical difference across the test plot is 2.95 cm with an inclination of less than 10 degrees (Figure A-1 in Appendix A).

Figure 1. Elevation map of the test plot, produced with lidar imagery having a 2.7926×2.7926 cm spatial resolution, identifying the coordinates for the center of the boxes for the 10×10 cell grid samples. DP is the deep plastic object (also referred to as Tmp33); DM is the deep metal object (also referred to as Tmp11); SM is the shallow metal object (also referred to as Tmp19); SP is the shallow plastic object (also referred to as Tmp13).

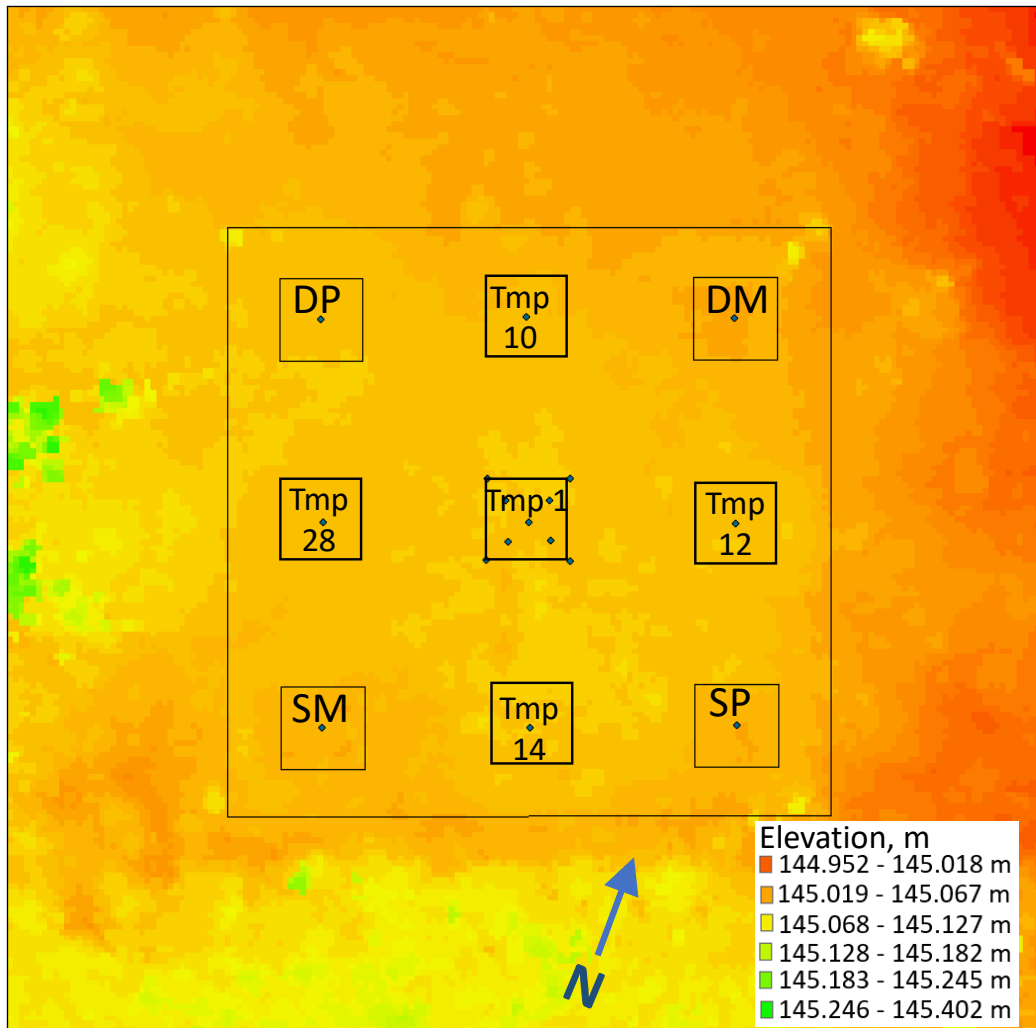


Table 1. Representative aspect categories.

Aspect Class	Aspect direction	Description
1	-1	Flat
2	0-22.5	North
3	22.5-67.5	Northeast
4	67.5-112.5	East
5	112.5-157.5	Southeast
6	157.5-202.5	South
7	202.5-247.5	Southwest
8	247.5-292.5	West
9	292.5-337.5	Northwest
1	337.5-360	North

Table 2. Elevation descriptive statistics for the lidar-derived data for the corresponding bounding boxes, with $n = 100$.

Bounding Box ID	Minimum (m)	Maximum (m)	Mean (m)	Standard Deviation (m)	Range (cm)
Tmp1	145.0837	145.0916	145.0874	0.001953	0.79
Tmp10	145.0776	145.0839	145.0817	0.001736	0.63
DM, Tmp11	145.0624	145.0713	145.0659	0.002164	0.89
Tmp12	145.0822	145.0919	145.0842	0.001976	0.97
SP, Tmp13	145.0722	145.0838	145.076	0.003777	1.16
Tmp14	145.0836	145.0923	145.0877	0.00221	0.87
SM, Tmp19	145.0673	145.0797	145.0745	0.002511	1.24
Tmp28	145.082	145.0851	145.0836	0.000523	0.30
DP, Tmp33	145.0826	145.0874	145.0843	0.001126	0.48

Table 3. Aspect descriptive statistics categories produced from the lidar-derived elevation data, with $n = 100$.

Bounding Box ID	Minimum (m)	Maximum (m)	Mean (m)	Frequency Distribution (%)							
				3	4	5	6	7	8	9	
Tmp1	3	8	5	6	24	23	30	15	2		
Tmp10	3	9	6	4	14	14	21	21	24	2	
DM, Tmp11	3	8	5	8	24	34	13	9	2		
Tmp12	3	9	6	1	9	16	36	18	15	5	
SP, Tmp13	3	7	4	1	58	36	4	1			
Tmp14	4	9	6		3	21	39	20	12	5	
SM, Tmp19	3	9	6	1	11	19	28	33	7	1	
Tmp28	3	8	6	1	5	20	50	18	6		
DP, Tmp33	3	9	6	4	18	24	15	20	15	4	

Table 4. Slope descriptive statistics in degrees produced from lidar-derived elevation data, with $n = 100$.

Bounding Box ID	Minimum (m)	Maximum (m)	Mean (m)	Standard Deviation (m)	Variance (m)	Standard Error
Tmp1	0.8989	8.4295	3.5480	1.5274	2.3329	0.0312
Tmp10	0.6483	4.4926	2.1399	0.9267	0.8587	0.0189
DM, Tmp11	1.1035	6.4571	3.4007	1.5157	2.2973	0.0309
Tmp12	0.8436	10.2064	2.5813	2.1815	4.7589	0.0445
SP, Tmp13	0.5603	7.1747	2.9991	2.1244	4.5129	0.0434
Tmp14	1.6410	8.5561	5.4840	1.3094	1.7146	0.0267
SM, Tmp19	1.7080	10.4513	5.4570	2.0851	4.3474	0.0426
Tmp28	0.6127	3.5293	1.7348	0.7217	0.5209	0.0147
DP, Tmp33	0.6375	4.2924	1.9407	0.8731	0.7623	0.0178

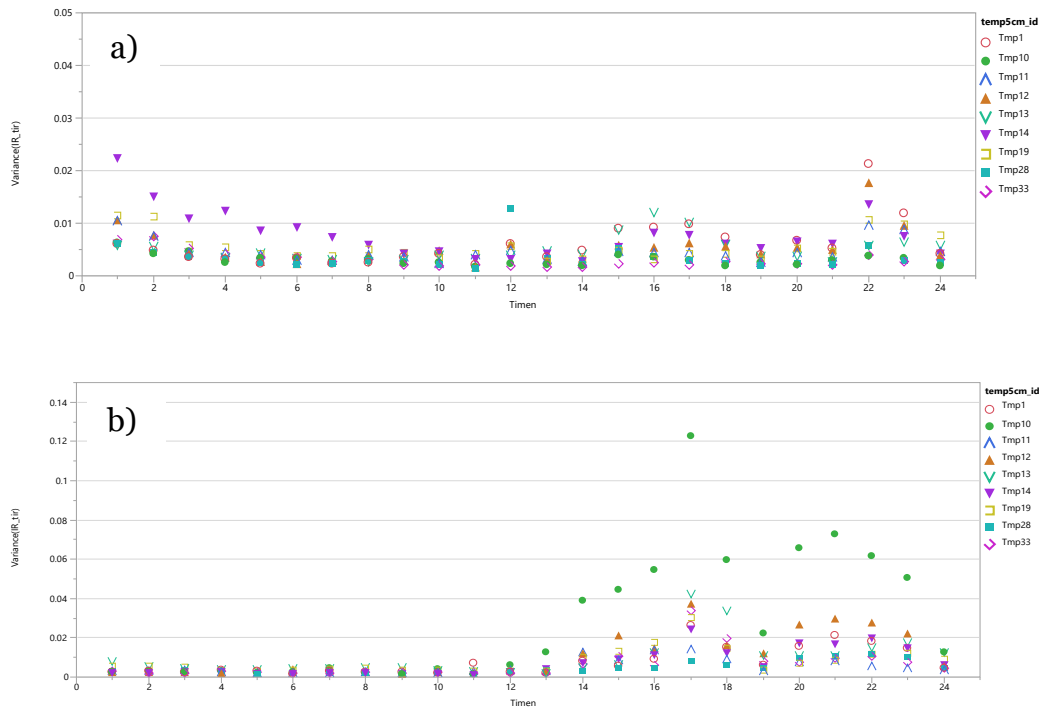
2.3 Statistical results

Appendix A shows the statistical distribution of the topographic characteristics for each bounding box in the test plot and the descriptive statistics of the datasets used in the analyses. Although the surface of the test plot is relatively flat, there are slight differences in aspect and slope. Most of the cells within the test-plot area face slightly east to southwest, receiving the most direct incoming solar radiation and subsequent substantial reflective thermal energy from midmorning to late afternoon on sunny days.

2.3.1 Temperature temporal variability

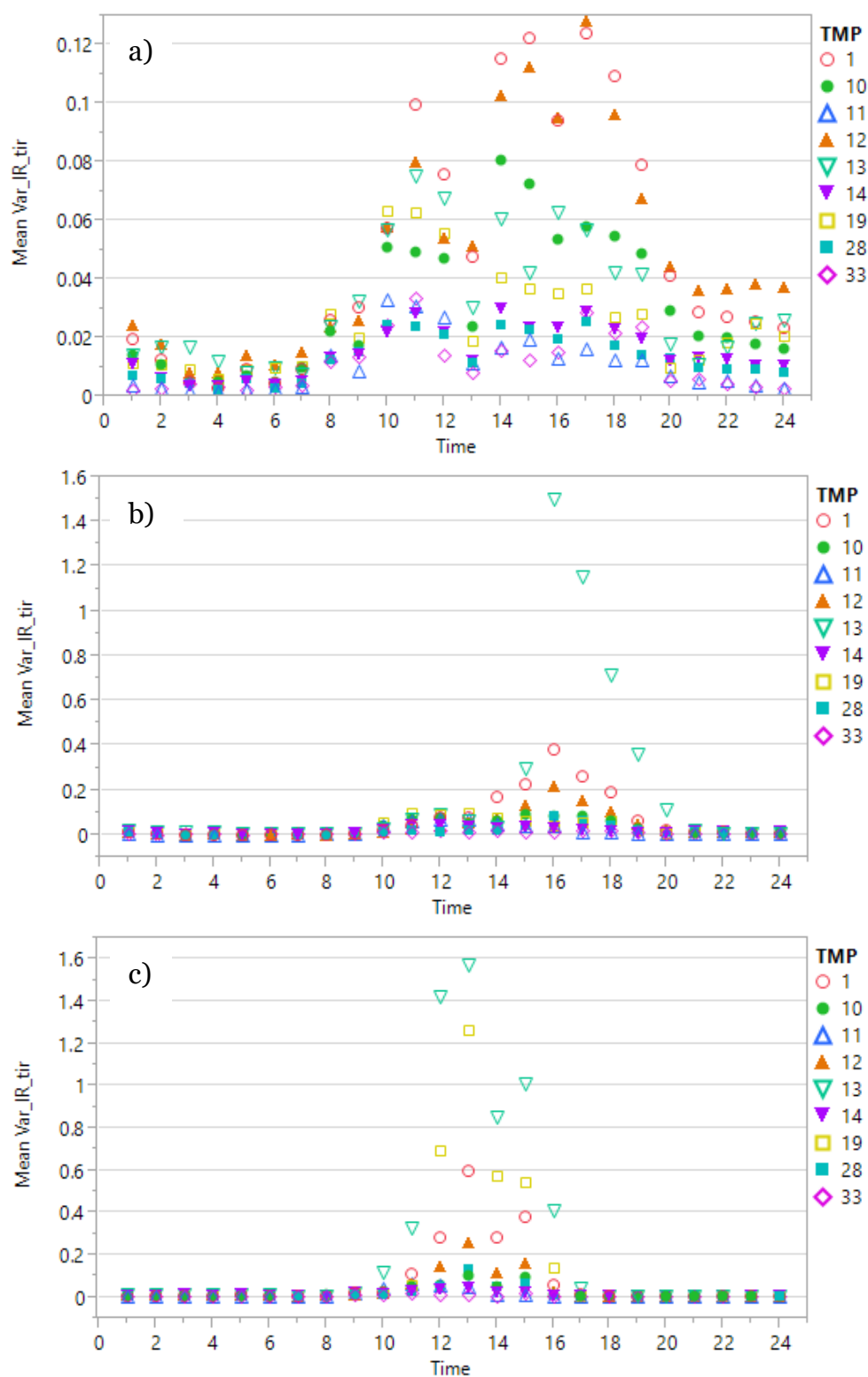
The overall hourly mean temperature distribution for the 15 July to 31 August 2018 dataset using one-way ANOVA analysis (Appendix B) indicates surface-soil temperatures at night are approximately the same for the entire test plot except for the Tmp13 (SP) bounding box, especially when the ground surface is cool. The dampening is likely due to condensation occurring with the soil above the SP object. The variance in surface-soil temperature at night is expected to be low due to the lack of incoming solar radiation. As the ground surface heats up, the mean soil-temperature distribution varies for all bounding boxes. However, these results are based on hourly mean temperature distribution. Some of the time, the thermal IR image response to the buried objects is clearly visible due to a difference in temperature between the surrounding background soil and the buried objects. Typically, the temperature response above the buried objects is manifested as a hotter surface soil than background areas. Following sunset and cooling of the surface soil, the pattern is reversed with the

Figure 3. Hourly variance on rainy days for (a) 17 July 2018 and (b) 22 August 2018, when the shortwave reflectance hovered below 69 W/m^2 for the Tmp11 (DM) object, Tmp13 (SP) object, Tmp19 (SM) object, and Tmp33 (DP) object.



On dry days, the variability of soil surface temperatures exhibits significant variation and deviation for all bounding boxes with the thermal noise (i.e., spatial temperature variance) differing from day to day and hourly. However, the spatial surface-soil-temperature variability patterns were not necessarily distinctive between object bounding boxes versus background bounding boxes. For example, on 29 July 2018, background locations (Tmp1, Tmp10, and Tmp12) depict more variation than the SP object (Tmp13) and the other buried objects (Figure 4, top) with 29 July 2018 being a typical mild and dry summer day. However, on a few dry and warm days (i.e., 6 and 7 August 2018, Figure 4, middle and bottom graphs), the variance of the soil-temperature responses above the SP object (Tmp13) was more pronounced than the background and other buried-object bounding boxes. In the absence of moisture, irregular ground-surface topography plays a more dominant role on surface-temperature variation.

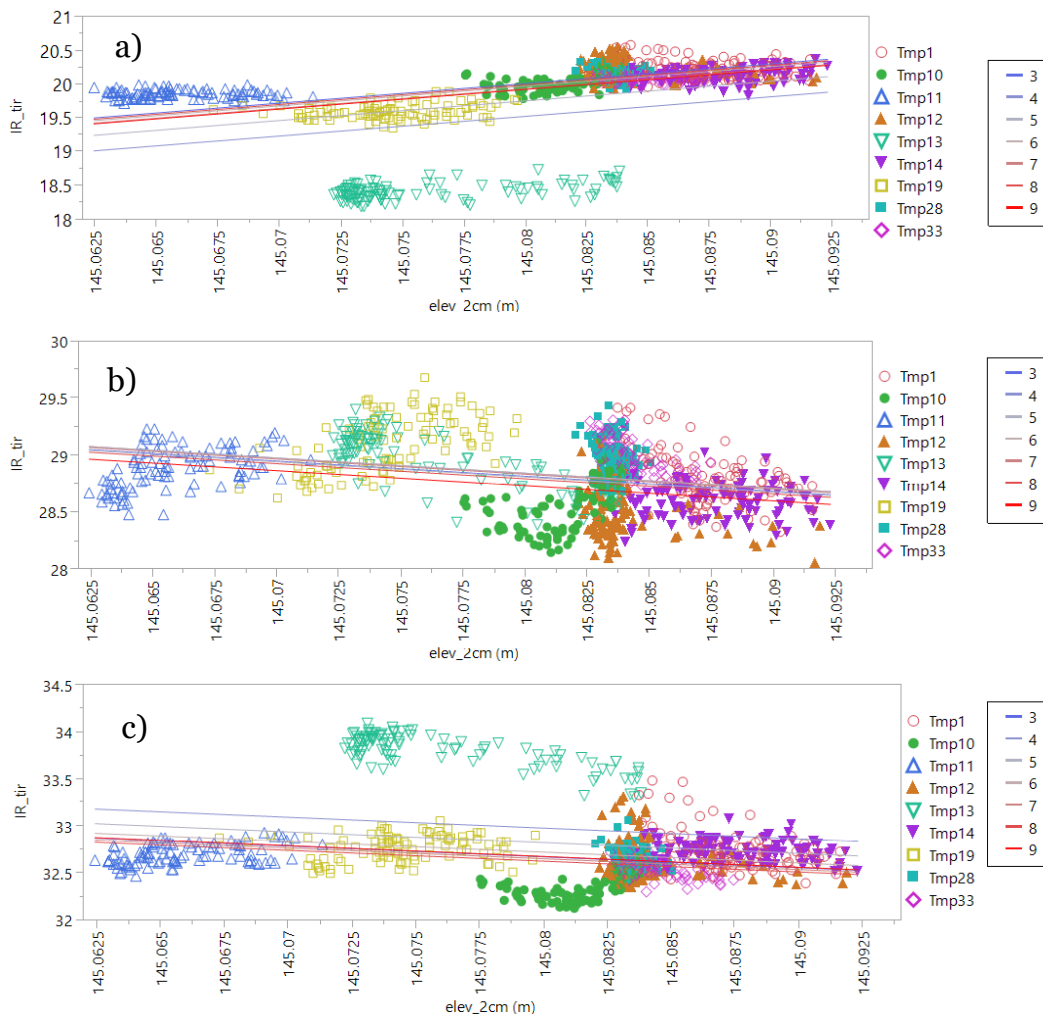
Figure 4. Mean hourly variance for (a) 29 July 2018, a mildly warm sunny day; (b) 6 August 2018; and (c) 7 August 2018 for the Tmp11 (DM) object, Tmp13 (SP) object, Tmp19 (SM) object, and Tmp33 (DP) object.



2.3.2 Influence of surface topography

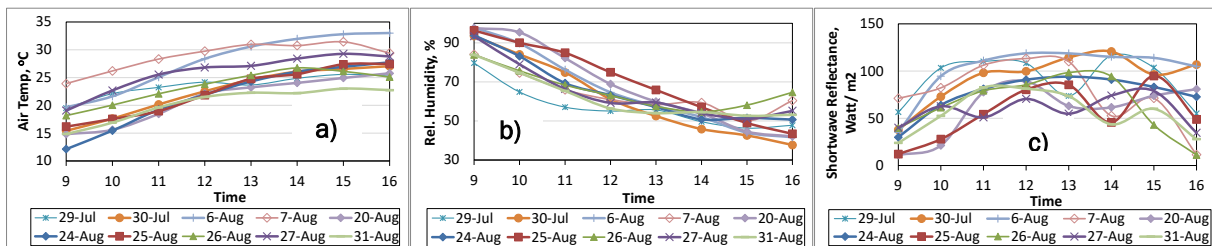
The DM (Tmp11) bounding box is at a lower elevation (Figure 5) within the test plot, while some of the background bounding boxes (i.e., Tmp1, Tmp12, and Tmp14) are at slightly higher elevations relative to the other bounding boxes (Table 2). The soil surface (thermal IR temperature responses within certain bounding boxes) is somewhat sensitive to elevation (Figure 5). The relationships between thermal IR temperature and elevation varied depending on the time of the day, although the topographic relief across the entire test plot is less than 3 cm. These thermal fluctuations are within the sensitivity of the IR camera and could potentially be the result of other variables beside elevation.

Figure 5. Surface-temperature (degrees Celsius) response as a function of elevation for 29 July 2018 at (a) Time 1, (b) Time 10 (middle graph), and (c) Time 13 with aspect class trend lines. Tmp11 is the DM object, Tmp13 is the SP object, Tmp19 is the SM object, and Tmp33 is the DP object.



The thermal noise as expressed by spatial thermal variability in surface-soil temperatures due to the influence of ground-surface irregularities when the ground was warm and dry was analyzed for the selected 10 rain-free days (Figure 6). The selected days included a change in atmospheric water-vapor content from very humid conditions in the midmornings to moderate humidity in the early afternoons. The shortwave reflectance varied as well from sunrise to sunset. The hourly mean air-temperature distributions of these selected days were relatively warm, typical of New England summer conditions. At 0900, the air temperature ranged from 12°C to 23°C with 7 August 2018 being the warmest morning. The top three warmest days were 6, 7, and 27 August. We analyzed the effect of topographic difference on surface-soil-temperature responses for each bounding box, separating the background bounding boxes from object bounding boxes during midday and early afternoon.

Figure 6. The (a) air temperature (°C), (b) relative humidity (%), and (c) shortwave reflectance (W/m²) for 29 and 30 July and 6, 7, 20, 24, 25, 26, 27, and 31 August 2018.



In Appendix C, Tables C-1 to C-6 summarize the correlation values and statistical significance (with $p < 0.05$) for the test-plot data obtained during warm and dry days from time 10 to 15. Tables C-1, C-3, and C-4. are arranged in ascending order (from lowest to highest) of the slope, β_b values; and Tables C-2, C-5, and C-6 are arranged in descending order (from highest to the lowest) of the slope, β_b values, with R^2 values from the summary of fit greater than 0.20. The statistical significance (p) is provided in the model, and only parameter estimates are reported in the results. Our null hypothesis is no relationship between the surface temperature and surface relief (elevation, slope, and aspect); the independent variable does not influence the dependent variables.

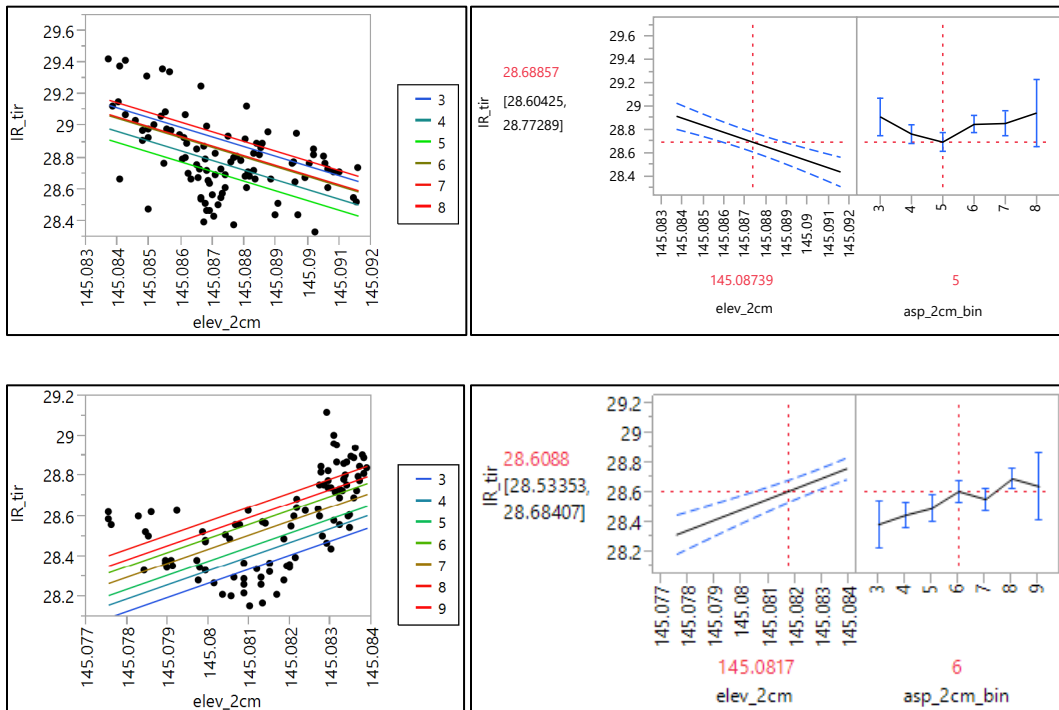
The slope of the ground surface has no correlation to soil temperature or elevation, which is not entirely surprising given the topographic relief of the test plot is less than 3 cm. The ground aspect appears to be a significant indicator of soil temperature derived from thermal IR imagery. The intercept, β_a , and slope, β_b , values reported in Tables C-1 to C-6 are

statistically significant (with $p < 0.05$). The intercept β_a represents the temperature value at minimum elevation, either along the southeast aspect for Tmp13 (SP) or along the south edge for the other bounding boxes. The overall orientation of the test plot may also play a role. The slope, β_b , denotes the temperature change from the minimum to maximum elevation (i.e., elevation range) at a selected aspect for the bounding box. A temperature change per 1 cm change in elevation is calculated to relate the magnitude of the temperature rise or reduction within the elevation range.

2.3.2.1 Background locations

The background bounding boxes revealed varying statistical outcomes, which are potentially due to their location within the test plot. The soil surface-temperature responses at Tmp1 and Tmp14 exhibited relatively warmer soil-surface pattern at lower elevations than surfaces at higher elevations. Consequently, the background bounding box data was combined to form a single reference point for comparing against disturbed bounding boxes (Figure 7).

Figure 7. Background surface-temperature (degrees Celsius) response as a function of elevation differences on 29 July 2018 at Time 10 for Tmp1 (*top charts*, $R^2 = 0.32$) and Tmp10 (*bottom charts*, $R^2 = 0.52$) locations. The *left* plots are regression plots with trends for the aspect class, and the corresponding *right* plots are prediction profiler plots for specific aspect classes.



With intercept, β_a , and slope, β_b , values of $p < 0.05$, the data for the undisturbed plots indicate no evidence that elevation affects soil surface temperature. Given that the elevation range is less than 3 cm, the small vertical relief has no effect on surface-soil temperature, but the overall ground-surface orientation could possibly play a role in explaining the thermal fluctuations.

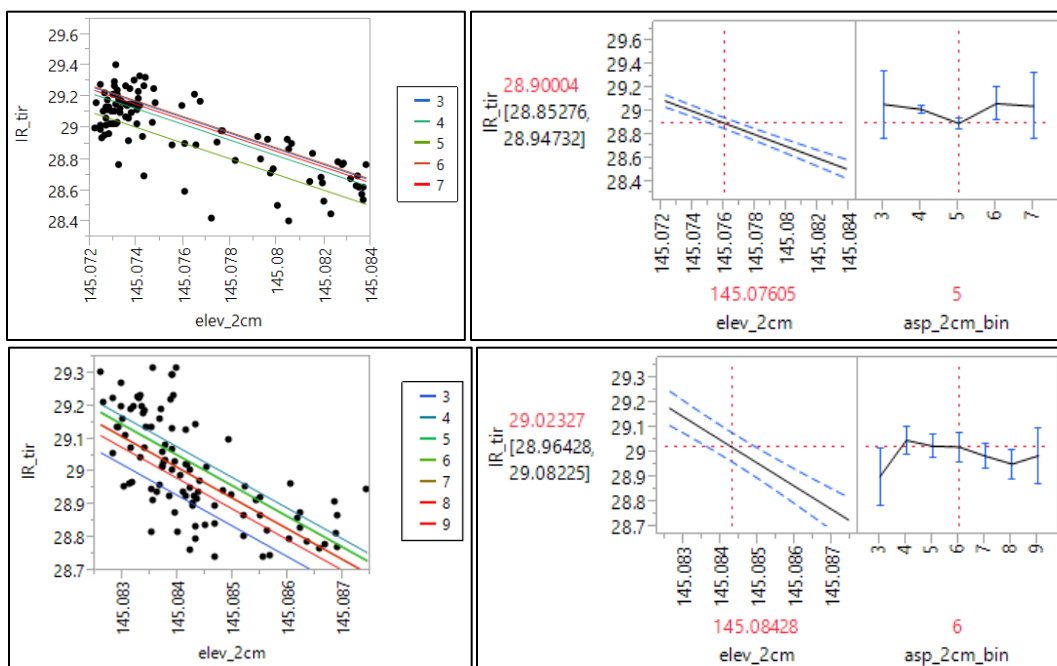
2.3.2.2 Plastic objects

The soil surface-temperature response of the 100 pixels for the SP object (Tmp13, Table C-3) and the DP object (Tmp33, Table C-4) showed statistical significance (intercept, β_a , and slope, β_b , values of $p < 0.05$) with elevation and aspect. The correlation (R^2) values were marginal (R^2 in the 0.75 range). These results suggest that the thermodynamic properties of the objects, including heat-transfer rates, have a stronger effect than surface microroughness. On a clear warm day with moderate relative humidity (i.e., 7 August 2018 at time 13), the temperature at higher elevations above the SP object was reduced by about 3.3°C (Table C-3). This pattern is like Tmp1 (background), where surface temperature at the intercept above the SP object was 7°C greater than for undisturbed areas (e.g., Tmp1). Trends seem to exist between surface temperature and elevation through midday and early afternoon (Figure 8) although probability estimates are not indicative that the surface relief at this scale directly affects the surface heating or cooling plastic. A significant number of cells were east and southeast facing (58% and 36%, respectively, Table 3) within the SP area. The soil surface-temperature distributions with statistical significance were between east and southeast aspect directions for the SP object area, and the surface directions exhibiting the highest temperatures were mostly east facing and, in some cases, northeast facing (Table C-3).

Overall, the soil surface temperature above the SP object was notably higher than the soil surface temperature above the DP object. One explanation is that the shallow object quickly equilibrates with the surface soil and then begins to absorb more heat. Unlike the metal objects, plastic objects cannot dissipate the heat rapidly, so the temperature of the plastic object and soil above increases. The deep objects may cause a temperature reduction as they temporally behave as a heat sink, absorbing heat from the surface soil as it tries to reach a new temperature equilibrium. The thermal heat capacity of the plastic objects, which are made from HDPE, is approximately 100–200 J/kg·°C higher than that of soil. The thermal conductivity of HDPE is anywhere from 8% to 40% that of soil as well.

While there appears to be statistical significance between elevation and surface temperature, the elevation ranges are very insignificant to play a role in the soil-temperature heating and cooling. The fundamental heat-transfer properties of the plastic objects likely are responsible for the heating and cooling of the overlying soil more than any changes in the surface microrelief are.

Figure 8. Surface thermal infrared (IR) temperature response as a function of elevation and aspect on 29 July 2018 at 1000, Tmp13 ($R^2 = 0.66$, SP object, *top* graphs); and Tmp33 ($R^2 = 0.50$, DP object, *bottom* graphs). The *left* plots are regression curves with trends lines for the aspect class, and the corresponding *right* plots are prediction profiler plots for the specific aspect class.

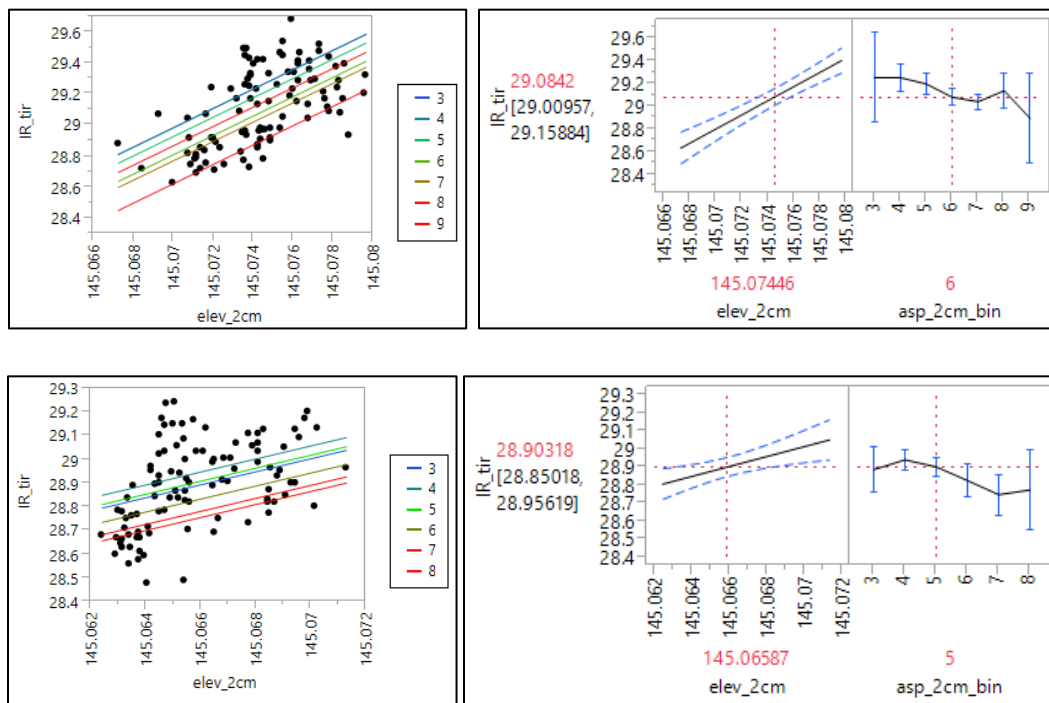


2.3.2.3 Metal objects

The trend between temperature and elevation during midday and early afternoon hours (Figure 8) for the pixels over the DM (Tmp11) and SM (Tmp19) objects indicates an elevated surface-temperature response at higher elevations. Again, the goodness of fit based on the R^2 values for the SM object (Tmp19, Table C-5.) and for the DM object (Tmp11, Table C-6.) range between 0.5 and 0.6, which is a marginal response due to the high variance in the data. However, the soil surface-temperature responses above the SM and DM objects revealed lower temperatures at lower elevations and higher temperatures at higher elevations (Figure 9). The pattern produced a 2°C temperature change over an elevation range of 1.24 cm for the SM bounding box on warm dry days near midday with moderate

relative humidity. Even though these results have statistical significance (intercept, β_a , and slope, β_b , values of $p < 0.05$) it seems unlikely that an elevation difference of a few centimeters is sufficient to affect heating or cooling of the surface. Yet, the results tend to support that the ground surfaces is generally warmer along the west and northwest side of the SM bounding box (Tmp19), with an exception on 29 July 2018 at 1000 (Figure 9, top right graph). In contrast, the higher ground-surface soil temperatures for the DM object is predominantly associated with west facing (Table C-6.) soil-surface slopes and a limited incident towards east-facing soil-surface slopes (Figure 9, bottom-right graph). These contradictory preferential heating results by surface orientation and elevation difference are likely within the temperature uncertainty of the IR camera.

Figure 9. Surface thermal IR temperature response due to elevation and aspect on 29 July 2018 at 1000 for Tmp19 ($R^2 = 0.42$, SM object, *top* graph) and Tmp11 ($R^2 = 0.32$, DM object, *bottom* graph). The *left* plots are regression curves with trend lines for the aspect class. The corresponding *right* plots are prediction profiler plots for specific aspect classes.



2.4 Summary and discussion

The surface-soil temperatures above the plastic and metal objects and even within the background bounding boxes exhibited varying responses by time of day (solar loading), meteorological conditions, the burial depth, and object composition. Soil-temperature variance within and between bounding boxes was generally low at night, due to the lack of incoming

solar radiation, and during or following precipitation events and periods of moisture condensation above the objects.

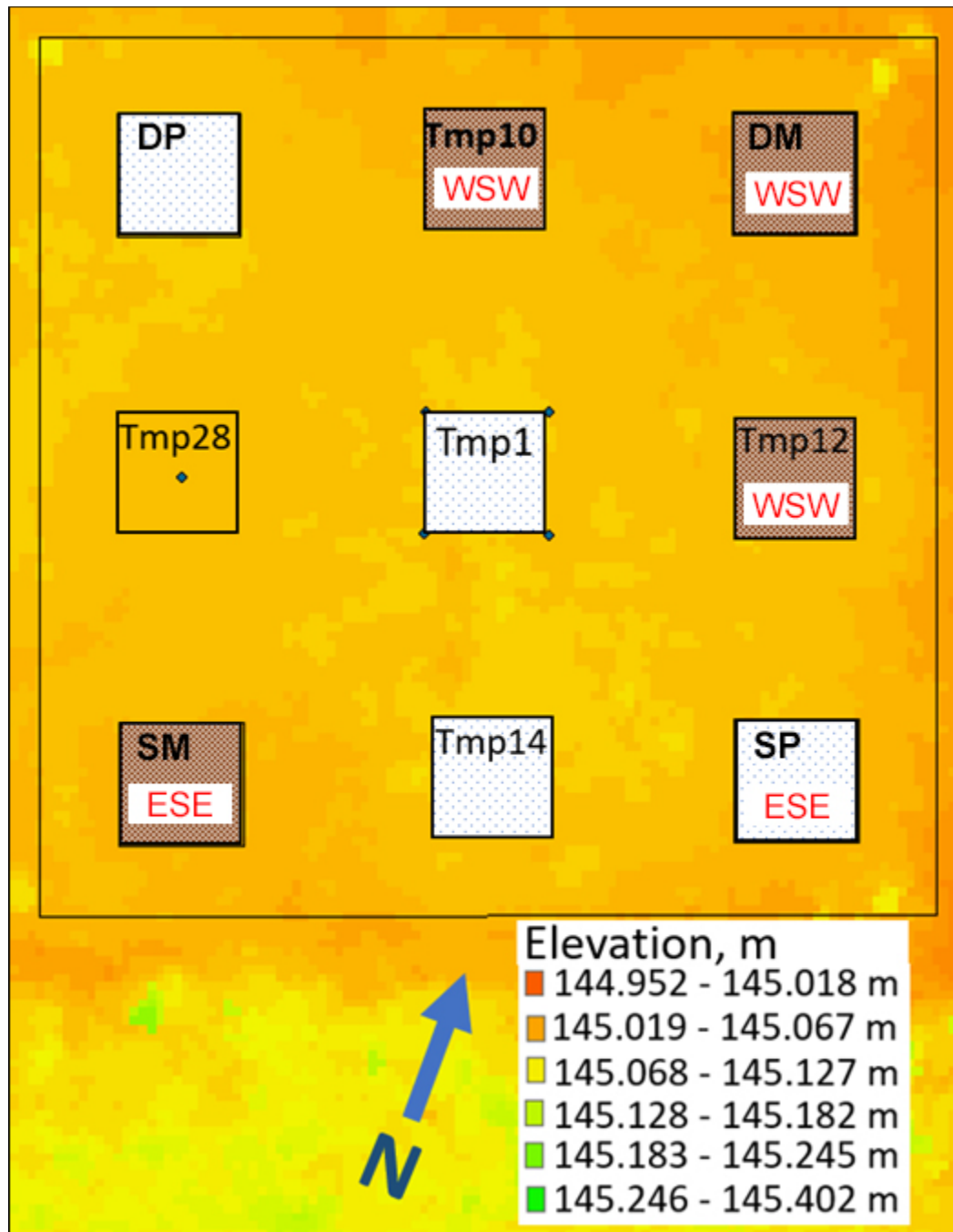
In contrast, the spatial variability of surface-soil temperature was more distinctive under dry meteorological conditions, particularly at noon and early afternoon. In addition, the spatial pattern of surface-soil temperature and magnitude of temperature response was clearly affected by the presence of buried objects. For instance, on a typical dry but mild summer day (i.e., 29 July 2018), the soil within the undisturbed area (specifically Tmp1, Tmp10, and Tmp12 locations; see Figure 10) depicted more variation in surface-soil temperatures than the SP object plastic (Tmp13). On warmer days, the variance of the soil-temperature response above the SP object was more pronounced than the undisturbed ground and other buried objects. This is due to the absorption and retention of thermal energy in the SP object. The thermal conductivity of plastic ranges from 8% to 40% that of soil. Greater energy transfer occurs at the shallower depth, resulting in a significantly greater response than from the deeper objects. The observed temperature reduction with the deep objects may be due to the objects behaving as a heat sink.

The difference between the metal and plastic objects can be attributed to their construction materials. Plastic materials are dielectrics, where thermal energy transfer is approximately four orders of magnitude smaller than that of metals. Consequently, the plastic objects cool more slowly than metal objects as well as heat more slowly. Greater energy transfer occurs at the shallower depth, resulting in a significantly greater response than from the deep objects.

Another source of surface-soil thermal variability or noise, as seen in the thermal IR imagery, is associated with the terrain surface. Locations of high or low temperatures within disturbed and undisturbed areas appear unrelated to changes in elevation or microrelief. These thermal variations are particularly prominent during midday and early afternoon hours when the ground is warm and dry. Given that the elevation difference between the disturbed and undisturbed areas is less than 3 cm, the small vertical relief likely has no effect on the heating and cooling of the soil surface. However, the ground-surface orientation could possibly play a role in the thermal fluctuations and preferential heating variability with surface orientation. However, the degree of temperature difference is likely within the uncertainty of the IR camera measurements. Moreover, variability in

soil hydraulic and physical properties as well as soil moisture at the sub-grid scale could be playing a role in generating noise.

Figure 10. Map of the test plots with bounding boxes shaded in *white* and *dark* shaded colors for elevation trends. DP is deep plastic (Tmp33); DM is deep metal (Tmp11); SM is shallow metal (Tmp19); SP is shallow plastic (Tmp13). (Note: *WSW* is *west-southwest*, and *ESE* is *east-southeast*.)



A small shack that housed the sensors for data acquisition and the concrete block supporting the tower for the IR camera are near the test plot. Tmp10 and DM (Tmp11) were located approximately 1 m south and 1.5 m southeast of the concrete block, respectively. The DP (Tmp33) was approximately 2 m southeast from the small shack. Reflective heating or cooling from these vertical objects could have some effect on the noise or inconsistencies of the soil temperatures, particularly on the test plots that are close to them. This is potentially the reason a predominant heating along west- and northwest-facing directions was observed on ground surfaces at higher elevations for TMP10, the DP object (for TMP11), and the SM object (Tmp19). The DM and SP object were possibly unaffected because their location was farther from the concrete base of the camera tower. Localized areas with a higher density of organic material and individual soil particles or granular materials with a particle size larger than the surrounding surface could also potentially contribute to unexpected temperature variability.

3 Freezing and Thawing Impacts on Target Recognition

As part of the current effort, we explored the effects of freezing and thawing on stationary AiTD/R as almost no information exists on this topic in the literature. Most of the research on AiTD/R performance has focused on developing AiTD/R contrast metrics for target identification using information captured by FLIR cameras in desert environments. As noted by Schachter (2020), FLIR sensors are noisy, and imagery assessments must account for this clutter. Target detection algorithms are directly related to negating this noise to aid in the identification of objects of interest. One type of AiTD/R contrast metric is based on the simplified t-test (Schachter 2020),

$$T = \frac{\mu_t - \mu_c}{\sqrt{\sigma_t^2 + \sigma_c^2}}, \quad (2)$$

where

T = t-test,
 μ_t = the target mean,
 μ_c = the clutter mean,
 σ_t = the target standard deviation, and
 σ_c = the clutter standard deviation.

Schachter (2020) lists over 250 different AiTD/R contrast metrics (T_n , $n = 1$ to 150). Besides the mean and standard deviation, other measures used are gray scale, interdecile ranges, and horizontal and vertical variation. Of these, Schachter identifies several dependent on the mean and standard deviations that perform particularly well:

$$T_5 = (\mu_t - \mu_c) / \sigma_c, \quad (3)$$

$$T_{14} = (\mu_t - \mu_c) / \sqrt{\sigma_t^2 + \sigma_c^2}, \quad (4)$$

$$T_{22} = \mu_t - \mu_c, \quad (5)$$

$$T_{42} = (\sigma_t - \sigma_c) / \sqrt{\sigma_t^2 + \sigma_c^2}, \quad (6)$$

$$T_{42} = (\sigma_t - \sigma_c) / \sqrt{\sigma_t^2 + \sigma_c^2}. \quad (7)$$

The US Army Combat Capabilities Development Command C5ISR has included four of these contrast metrics (T_1 , T_5 , T_{10} , and T_{14}) as well six other contrast metrics on a handheld graphical user interface they developed for use in the field. The AiTD/R contrast metrics we used (M_{Nn}) are:

1. M_1 : Michelson contrast: $C_m = \frac{\mu_t - \mu_b}{\mu_t + \mu_b}$.
2. M_2 : Adjusted Michelson contrast: $C_{ma} = \frac{\mu_t - \mu_b}{\mu_t + \mu_b - 2 * \min_i}$.
3. M_3 : Root sum of squares (RSS) contrast: $C_{RSS} = \frac{\sqrt{(\mu_t - \mu_b)^2 + \sigma_t^2}}{\mu_t - \mu_b}$.
4. M_4 : $T_1 = \frac{\mu_t - \mu_b}{\sqrt{\sigma_t^2 + \sigma_b^2}}$.
5. M_5 : $T_{10} = \frac{\mu_t - \mu_b}{\sigma_i}$.
6. M_6 : SNR: $T_5 = \frac{\mu_t - \mu_b}{\sigma_b}$.
7. M_7 : $T_{14} = \frac{\mu_t - \mu_i}{\sqrt{\sigma_t^2 + \sigma_i^2}}$.
8. M_8 : Decision-theoretic rough sets: $T_{dTrss} = \sqrt{(\mu_t - \mu_b)^2 + \sigma_t^2}$.
9. M_9 : $T_{dTrss} = \frac{\sqrt{(\mu_t - \mu_b)^2 + \sigma_t^2}}{\sigma_b}$.
10. M_{10} : $T_{dTrss/\sigma_i} = \frac{\sqrt{(\mu_t - \mu_b)^2 + \sigma_t^2}}{\sigma_i}$.

The subscript i is for the entire image (240×320 pixels), and b is the background or clutter. For the purposes of this study, we used the surface-soil temperature (Kelvin) as the primary physical property. These were obtained by converting the measured A310 F90 FLIR Systems Inc. camera radiances to temperatures by using the method outlined in Clausen et al. (2022). The images used were collected over a 3×3 m area in which two metal and two plastic objects were buried at 5 cm (shallow) and 25 cm (deep) (Clausen et al. 2022). In the present study, we used data collected immediately after the objects were buried in July 2018 through April 2021. Means and standard deviations for the targets were calculated on an area of 3×3 pixels centered on the four buried targets. The background is defined as an area of 3×3 pixels in the center of the image.

Section 6 discusses the development of a new contrast metric, Bragdon (M_B), based on the sum of the reprojected principal component analysis (PCA) of metrics M_1 , M_2 , M_5 , and M_6 . Following this approach, we used the same method to develop metrics M_6 , M_7 , $M_{11} = T_{22}$, and $M_{12} = T_{42}$ based on Schachter's (2020) findings (M_S). Before performing PCA analysis using the variance-covariance matrix and variable weights, we standardized the contrast metrics by subtracting the means and then dividing by the standard deviations. There are as many principal components as there are variables. The principal components are a linear combination of the eigenvectors of the covariance matrix with the first principal component accounting for the largest possible variance and each remaining component accounting for ever less variance and being perpendicular to the others (Jaadi 2021). Figure 11 displays the resulting variances and percent explained for the Bragdon (Section 6) and Schachter PCA over the four buried objects (SP, SM, DP, and DM). Figures 12 and 13 are the biplots and loading plots for the two approaches, respectively; and Figure 14 shows the correlations between the principal components and contrast metrics.

Scree plots (Figure 11) typically increase steeply; and as the number of components increases, the curve levels off (Ngo 2018). Where the curve levels off, commonly referred to as bending, determines the number of principal components needed. Usually, principal components that describe at least 80% of the variance and whose eigenvalue is at least 1 are retained. In the loading plots, the closer the lines between different variables, the more closely the correlation of the variables.

Figures 11a and 11b bend at the second principal component, indicating only one component is necessary to explain 85% of the variance. Figure 12 corroborates the findings in Figure 11a and 11b with the collapsed nature of the reprojected contrast metrics along the first component axis. In Figure 12, it is evident that M_1 , M_5 , and M_6 are highly correlated with one another while M_2 is uncorrelated with the others, indicating that not all the contrast metrics are required. For Schachter's metrics, the scree plots (Figure 11c and 11d) are not as steep, and it can be argued that two components are sufficient to describe the data to the same level as the M_B contrast metric discussed in Section 6. The grouping of the reprojected contrast metrics is more dispersed for the Schachter contrast metrics than the M_B contrast metric as seen in Figure 13, especially for the SP target. Also, M_6 and M_{11} are highly correlated, and both are similar in behavior to M_7 while M_{12} is uncorrelated with the rest.

Figure 11. Plot of eigenvalues and variance explained for (a) Bragdon principal component analysis (PCA) eigenvalue, (b) Bragdon PCA percent variance explained, (c) Schacter PCA eigenvalue, and (d) Schacter PCA percent variance explained.

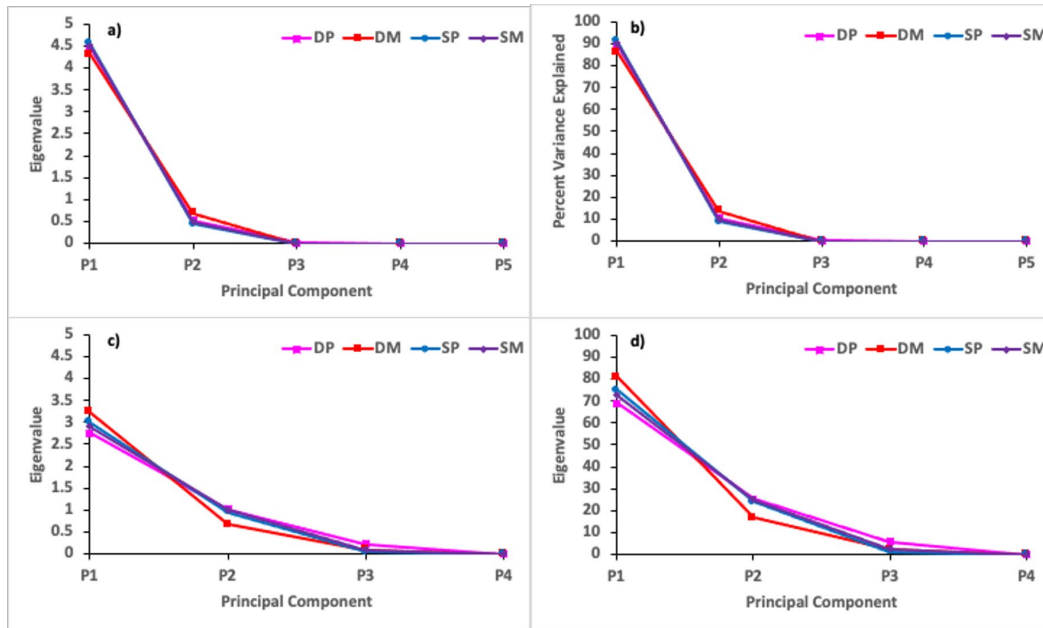


Figure 12. PCA biplot of standardized metrics used by Bragdon reprojected on the first two principal components. *Blue lines* are the principal component loads, and *red dots* are the scores for the (a) DP object, (b) DM object, (c) SM object, and (d) SP object.

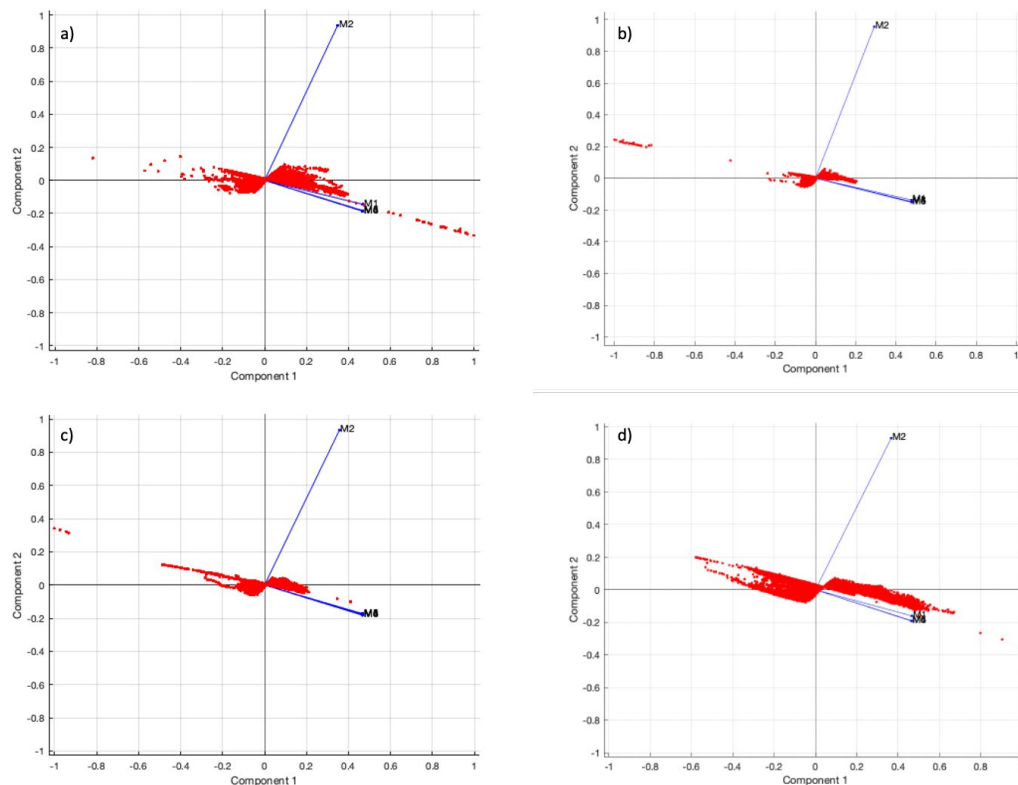


Figure 13. Standardized metrics deemed important by Schachter reprojected on the first two principal components for the (a) DP object, (b) DM object, (c) SM object, and (d) SP object.

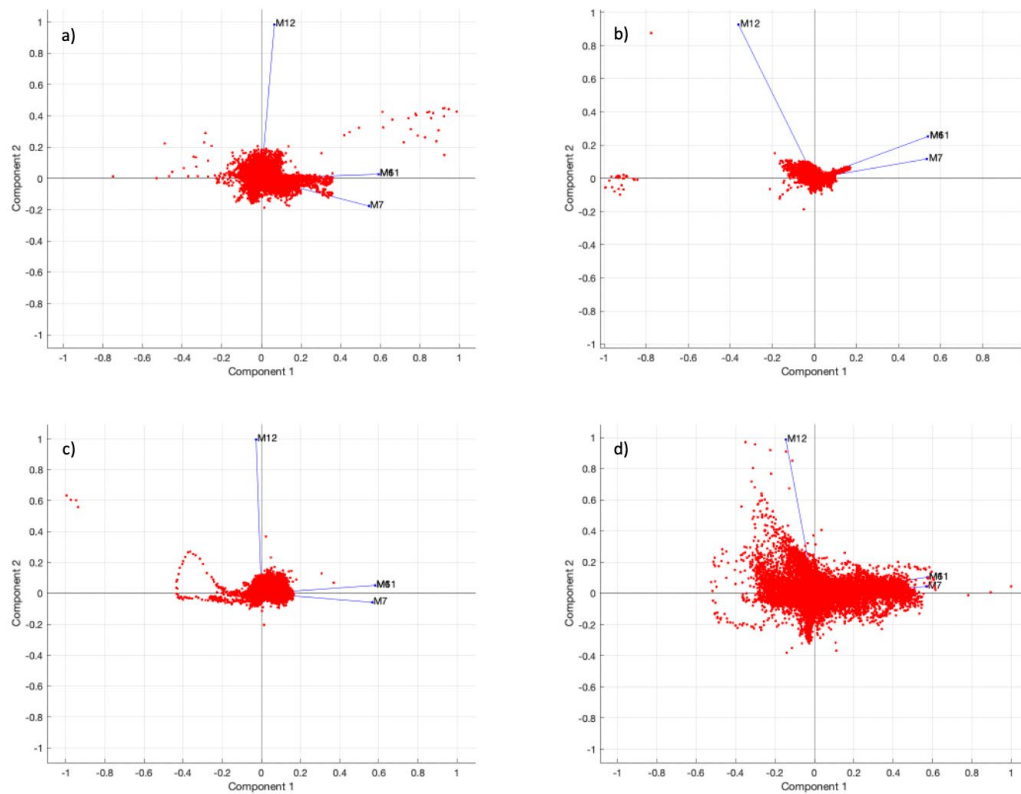
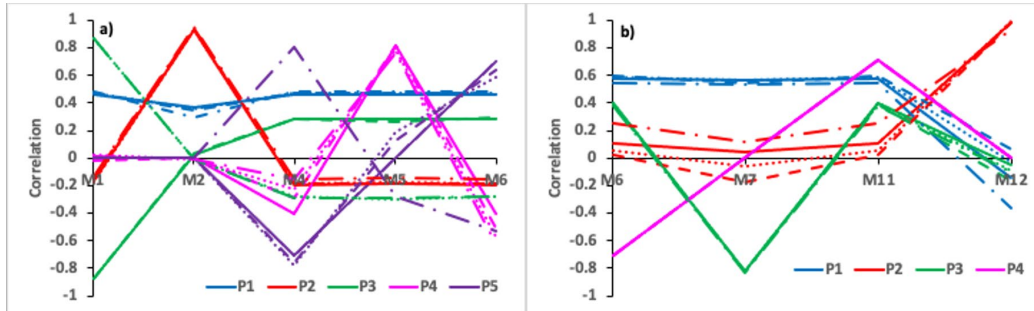


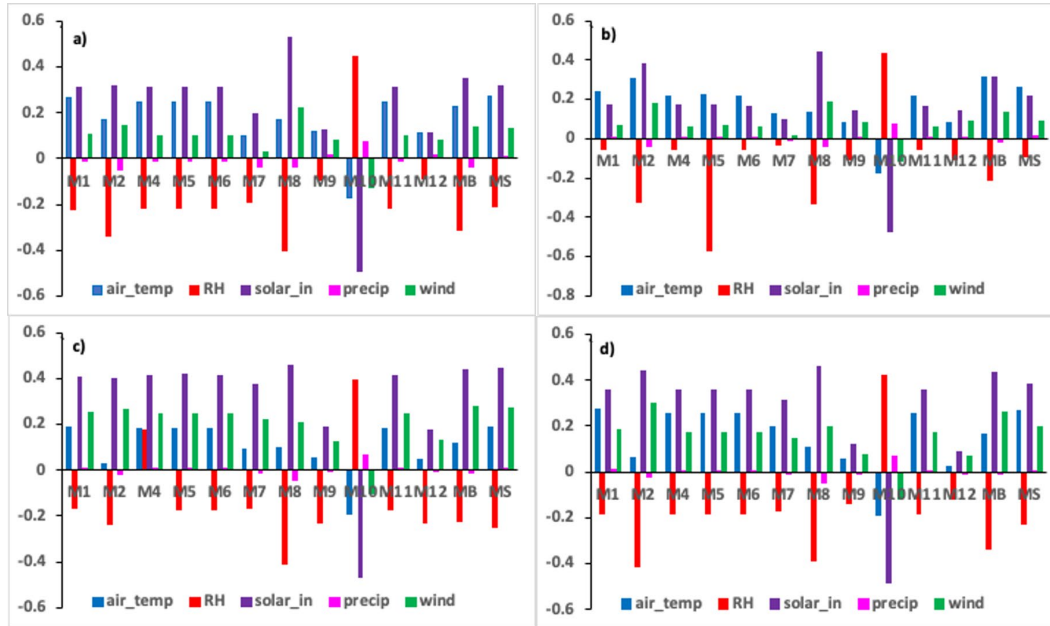
Figure 14 shows the correlation of each of the contrast metrics to the principal components for both the M_B and M_S contrast metrics. Although the first principal component does not have the largest correlation, it is, on average, larger than the rest of the principal components for the M_B contrast metric (Figure 14a). This is also true for Schachter's contrast metrics except for M_{12} , where the second principal component dominates. Unlike for the M_B method, more spread is apparent between the four targets for Schachter's contrast metrics, especially with the second principal component. From the above discussion, it appears the Bragdon method is preferable and that both methods can be simplified by reducing the number of contrast metrics included. For Schachter's contrast metrics, M_{12} , M_7 , and either M_6 or M_{11} should be retained, while for Bragdon's contrast metrics, M_2 and either M_1 , M_4 , M_5 , or M_6 should be kept.

Figure 14. Profile plot of principal component correlations for (a) Bragdon metrics and (b) Schachter metrics. The *dashed line* represents the DP object, the *dash-dot line* is the DM object, the *solid line* is the SP object, and the *dotted line* is the SM object.



With this understanding of the PCA-based contrast metrics, we now investigate how those metrics, as well as the ten C5ISR metrics included in their graphical user interface software, depend on weather-forcing parameters. Before performing the correlation calculations, we standardized all metrics and weather parameters. Section 6 found that inclusion of soil moisture, air temperature, incoming solar radiation, relative humidity, and air pressure greatly improved ML classification. Our analysis does not consider soil moisture because the closest probes were 15 cm below the surface. We treated precipitation events as a proxy for air pressure and soil moisture. Besides parameters found important in Section 6, we also investigated wind speed dependence. Figure 15 shows the results of our covariance analysis of contrast metrics for all four objects. This analysis used only snow-free time steps, resulting in 70,661 images. From Figure 15, it is evident that incoming solar radiation is the dominant indicator for most metrics and is positively correlated with all metrics except for M_{10} . Precipitation appears to have the least correlation with the metrics investigated. For the plastic objects, relative humidity is the next most important factor for metrics M_2 , M_8 , M_{10} , and M_B , while air temperature and wind speed are next. For the metal targets, relative humidity has the next most influence for metrics M_8 and M_{10} . For all targets, M_7 , M_9 , and M_{12} are least affected by weather.

Figure 15. Covariance of contrast metrics for M_1 to M_{12} , M_B , and M_S for standardized air temperature, relative humidity (RH), incoming solar radiation (solar_in), precipitation, and wind speed for the (a) DP object, (b) DM object, (c) SM object, and (d) SP object.



As stated earlier, of special interest to this investigation are the dependencies of the contrast metrics on soil freezing and thawing. Based on the above findings, bivariate plots of M_2 , M_8 , M_{10} , M_B , and M_S to the mean image temperature are evaluated for differences between frozen and unfrozen AiTD/R contrast metrics. Previous studies (Clausen et al. 2021) found the SP object to have the greatest impact on surface-soil temperatures, and so Figure 16 shows results for only this target. Figure 16 presents the results for M_2 , M_8 , and M_{10} while Figure 17 show the plots for M_B and M_S . The highest image counts (contrast-metric values that occur most as a function of temperature, darkest red boxes) occur when the background and target center mean values are equal and the target temperatures are uniform such that $\mu_t - \mu_b = 0$ and $\sigma_t = 0$. For M_2 , this coincides when the mean image temperature is near freezing. For metrics M_8 and M_{10} , there is a second peak near 25°C. This second but smaller peak is also seen in the M_B and M_S metrics (Figure 17). This second peak is also more pronounced for the other targets. For the wind speed and incoming solar radiation, the plots are more normalized with the peaks occurring at 0, while for relative humidity, the shape was reversed in that the peak is at 100%. For most metrics, there were no secondary peaks.

Figure 16. Bivariate plots of the contrast metrics (a) M_2 , (b) M_8 , and (c) M_{10} and mean image temperature for the SP object. Colors correspond to normalized radiance counts.

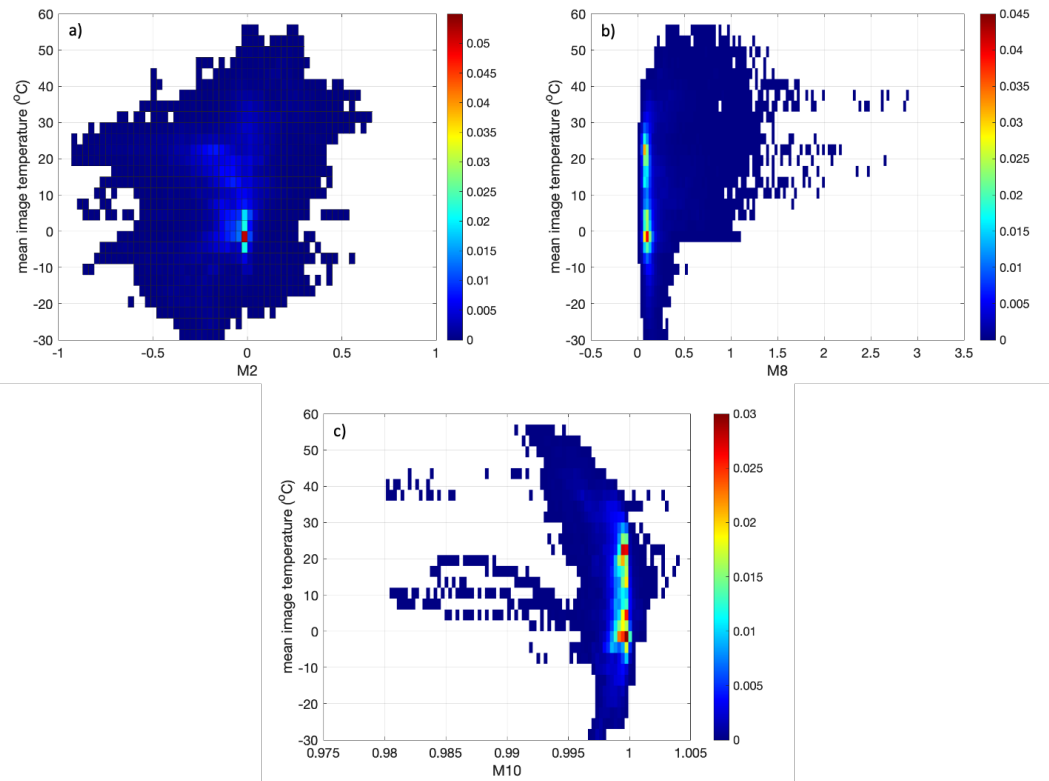
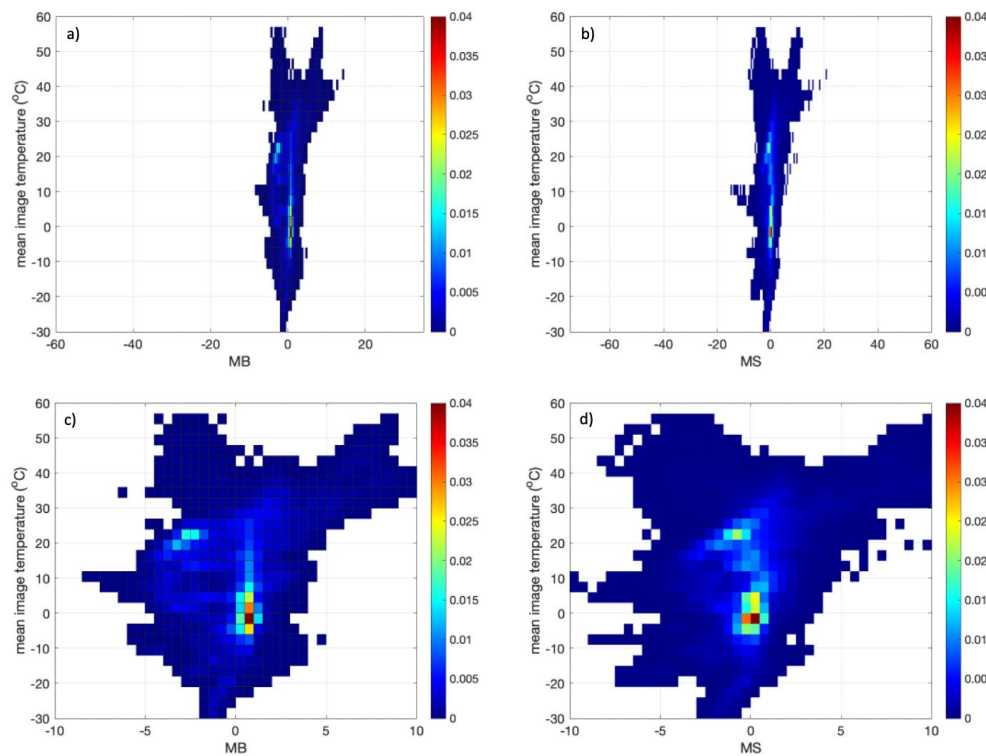


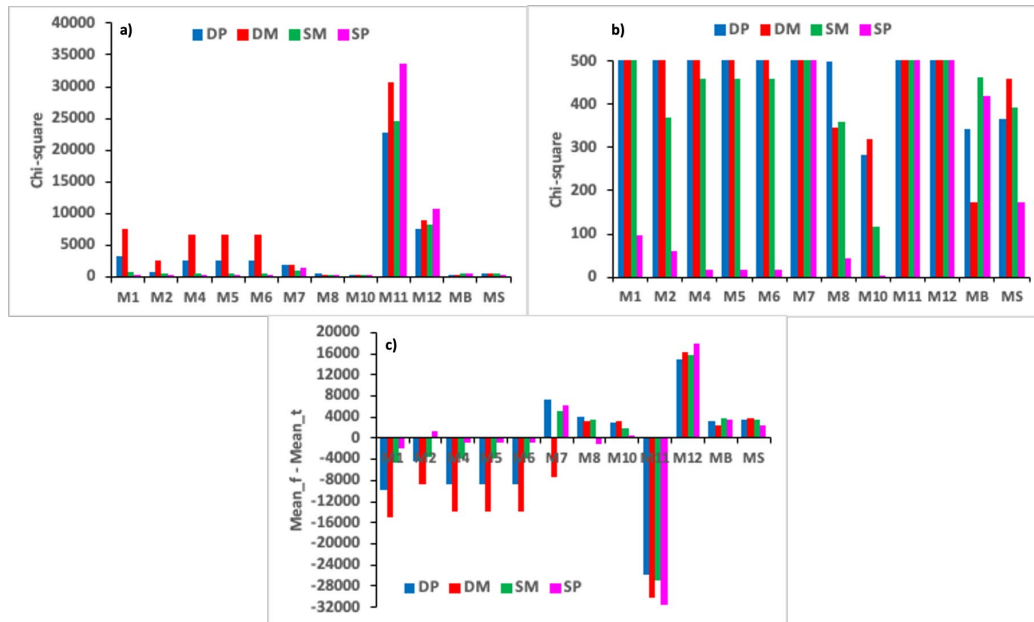
Figure 17. Bivariate plots of metrics for M_B (a) full and (c) partial and M_S (b) full and (d) partial and mean image temperature for the SP object. Colors correspond to normalized counts.



Although contrast-metric indicators sensitive to freezing are potentially helpful, the bivariate plots of the contrast metrics are not enough to show differences between frozen and unfrozen conditions. Therefore, an ANOVA was performed for M_S , M_B , and the C5ISR metrics for the four buried objects. To do this, we divided the data into two groups based on the mean image radiative temperature: (1) greater than or equal to the freezing point (273.15 K) and (2) less than 273.15 K. This resulted in 51,176 images with unfrozen soil and 19,485 images when the soil was frozen. Data analysis was performed using the nonparametric ANOVA (Kruskal-Wallis) technique because the frozen data median values better captured the peak in the metric histograms and could handle outliers better even though the sample sizes were large (Frost 2021). Figure 18 presents for all four objects the chi-square (χ^2) test of independence values and difference of means for the two groups. Except for M_4 and M_6 for which $p = 0.001$ and M_{10} where $p = 0.3739$ for the SP object, all other p -test values were equal to or nearly zero. Thus, the metric values for frozen and unfrozen conditions have the same distributions except for these cases. This is reiterated in Figure 18b where χ^2 is smallest for M_{10} , especially for the SP object. This is the only metric where $\chi^2 < 1$. Also observed is that the χ^2 values for this target are smaller than for the other targets for all metrics except M_{11} and M_{12} . Also noted in Figure 18a is that metrics M_{11} and M_{12} have the largest χ^2 values. Figure 18c presents the difference in means of the ANOVA sum of squares of the metrics between frozen and unfrozen conditions. The largest differences for all buried objects are metrics M_{11} and M_{12} . For the other metrics, the difference is much smaller.

From the above discussion, it is evident that there is a difference in all tested contrast metrics between the frozen and unfrozen soil. However, contrast metrics M_{11} (difference in means) and M_{12} (difference in standard deviations) are especially promising even if they are not the most sensitive to weather forcing. These same metrics had the most variance in the PCA analysis. As the soil freezes, the difference in mean IR temperature over the objects and the background disappears.

Figure 18. Nonparametric analysis of variance results for frozen and nonfrozen images: (a) chi-square, (b) chi-square zoomed in, and (c) difference between mean frozen and mean nonfrozen metric values.



4 Thermal Modeling

During this subtask, we observed the thermal signatures of buried objects by comparing them to a control section (center of the plot) by using both the thermal IR images and measured soil-temperature measurements at 5 cm bgs. The collection of thermal images analyzed in this study includes imagery from 14 July 2018 to 15 November 2018 and 15 April 2020 to 15 May 2020. The 5 cm bgs soil temperatures analyzed were from 14 July 2018 through 15 May 2020. More details about the imagery and soil-temperature collection can be found in Clausen et al. (2021).

We collected thermal IR images at a time step of 5 minutes, and we averaged the radiance values from a 3×3 -pixel area above each object and control and converted to temperature. The conversion uses meteorological and physical properties (e.g., air temperature, relative humidity, and camera height) and is described in detail in Clausen et al. (2021). Our thermal signature comparison was performed for different average air temperatures to understand how lower temperatures (freezing and thawing) influence object detection.

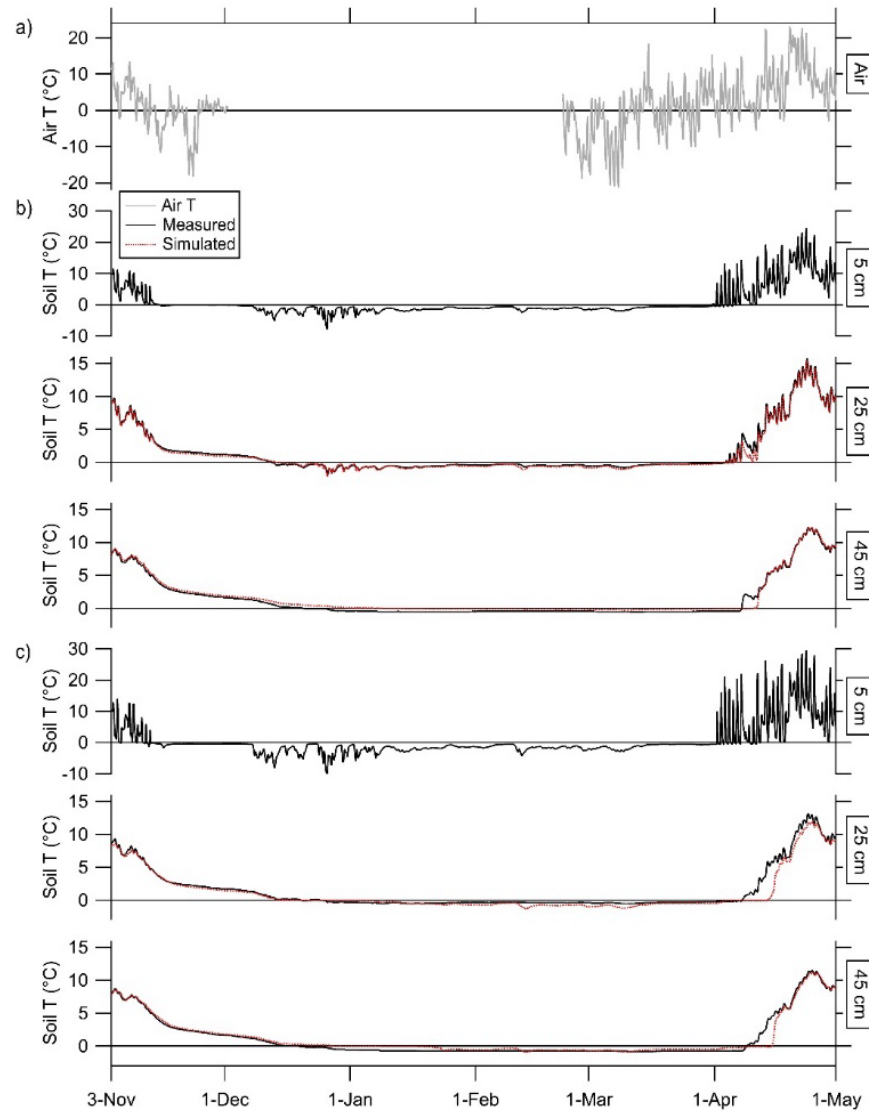
Because the thermal-imagery dataset was limited during low temperatures due to snow cover and inadvertent camera shutdown, we also compared the soil temperatures measured at 5 cm bgs (above each object and control). The measurements were collected at a time step of 15 minutes. The differences in thermal signatures between the objects and control were binned hourly for each time (warm, cold, and thawing).

For the soil thermal-modeling effort in this subtask, we performed simulations over the four objects and a control (center of the plot) during both freezing (November 2018) and thawing (April 2020). We used the SVHEAT SoilVision CONNECT V10.04.00.135, a finite element software by Bentley Systems Incorporated (Exton, PA); and the model setup included a 1 m wide and 65 cm deep two-dimensional soil section for each section. Clausen et al. (2022) provides more details about the model.

To calibrate the soil modeling at low temperatures, we used the soil measurements at the control and SP object to force the model. The calibration simulations were performed for a total of 179 days (3 November 2018 to 1 May 2019) using a time step of 15 minutes (Figure 19). For the calibration, the vertical total depth of the soil section was 60 cm; and to force the

models, we used the 5 and 65 cm bgs soil measurements as the top and bottom boundary conditions, respectively.

Figure 19. Measured (*black*) temperatures in comparison to simulated (*red dashed*) for 3 November 2018 to 1 May 2019 for (a) air temperature (T, *gray*), and soil temperatures for the (b) control and (c) SP object at a depth of 5, 25, and 45 cm bgs. Note the different scales on the y-axis.

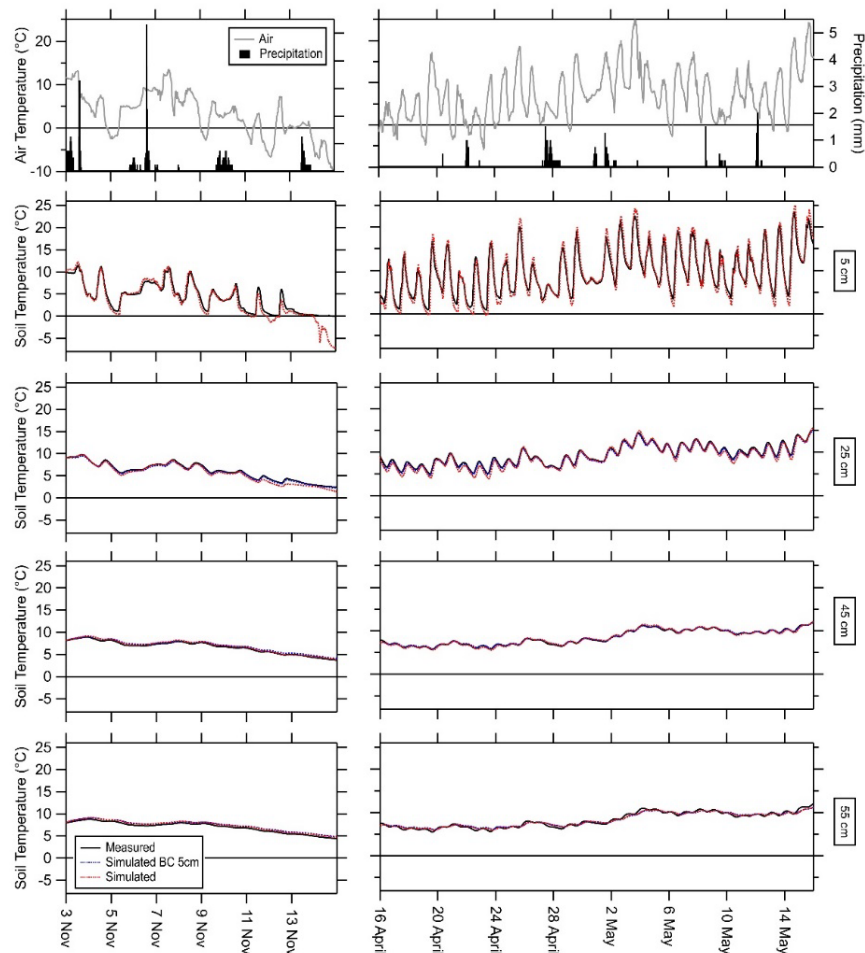


The calibration simulations included varying thermal conductivity of the unfrozen and frozen state of the soil. Initial thermal conductivity values were based on soil testing conducted by GSL (Clausen et al. 2022). The model-simulated soil temperatures matched the measured temperatures for an unfrozen and frozen soil with thermal conductivity of 2.1 W/mK, one of the higher values measured during laboratory testing. Other material properties used were a soil dry density of 1,876 kg/m³ and specific heat

capacity of 1,066 J/kg °C. We also applied a phase-change temperature from -0.01°C to -0.1°C . Because the initial model simulated and measured temperatures are close, we used these soil properties for the remaining simulations discussed in this section.

To investigate the accuracy of the converted thermal IR temperatures and to further confirm the model parameters, we ran additional simulations using the thermal IR temperatures as the forcing temperature at the boundary condition (Figure 20). Simulations were for 12 days during soil freeze-up (3 November to 15 November 2018) and 30 days at soil thaw (15 April to 15 May 2020). In general, there is a good match between measured and simulated values, but it appears that the measured IR radiance values converted to temperature are less accurate at low temperatures.

Figure 20. Air temperature (*gray line*), precipitation (*black solid bars*), measured soil temperatures (*black line*), and model-simulated soil temperatures (*red dashed line*) at 5, 25, 45, and 55 cm bgs for a freeze-up (*left panels*) and thaw (*right panels*).

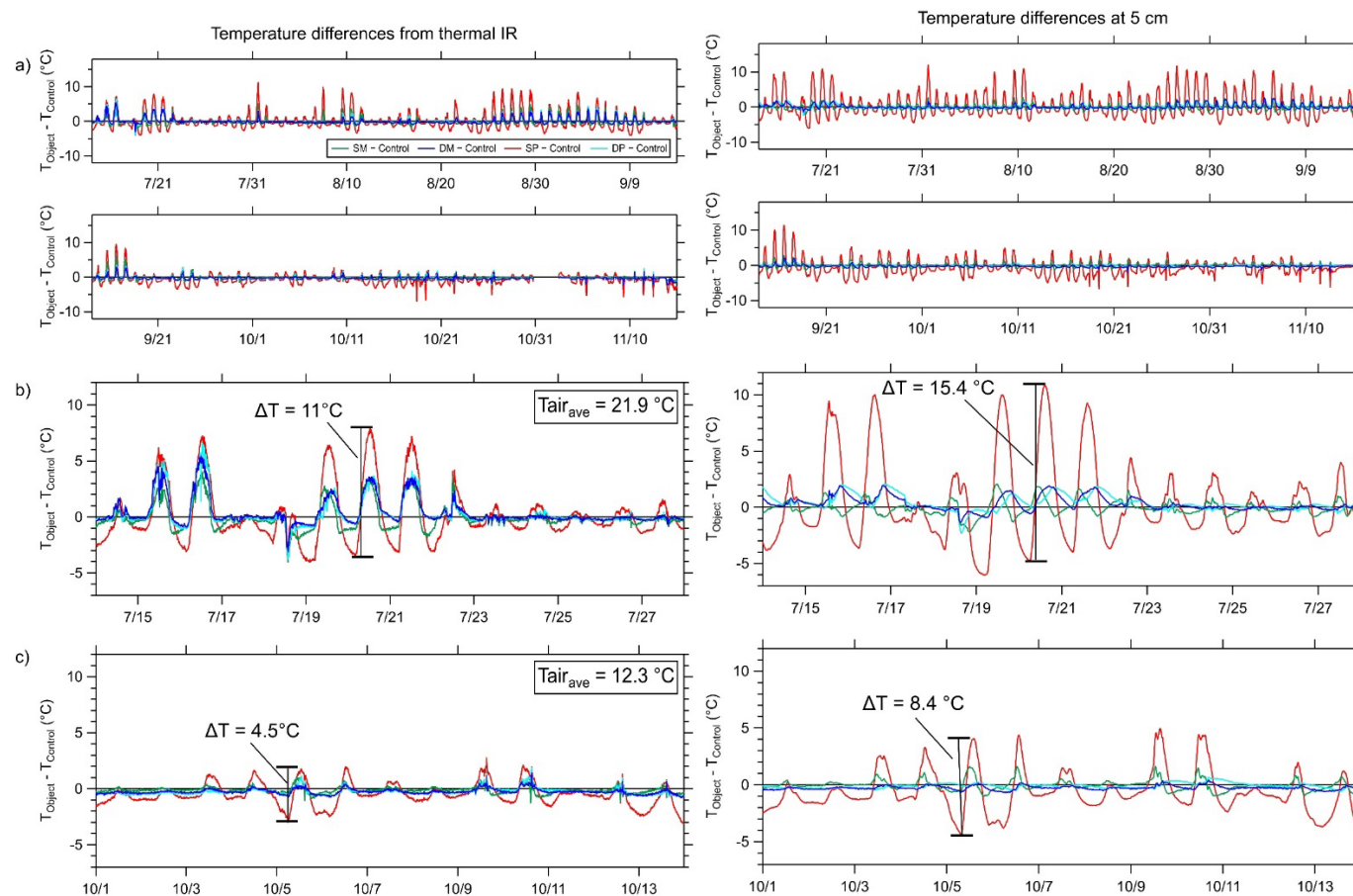


4.1 Soil-temperature response of buried objects during low temperatures

We investigated the thermal soil signature directly above the buried objects and compared it to the control by using several methods. Because there was a limited collection of thermal imagery during lower temperatures, we also analyzed the 5 cm bgs soil-temperature measurements. During the calibration of the thermal model (Figure 19), we found a possible bias for the radiance values converted to temperatures during cold conditions. Results from these simulations indicate that the thermal IR radiance values converted to temperatures are in close agreement during higher temperatures (also confirmed in Clausen et al. 2022), but the conversion during freezing temperatures overestimates the temperatures (to lower than actual temperatures). At this stage we do not have an explanation for this model overestimation.

Figure 21 (left panels) shows a comparison of thermal IR temperatures above each object when compared to the control (middle of the test plot) in 2018 (14 July to 15 November). The difference in IR temperatures varies depending on object, time of the day, time of the year, and other environmental factors (e.g., air temperature, precipitation, and cloud cover). Smaller temperature differences between the object and control are evident during lower temperatures (Figure 21a–c). In general, there is a diurnal difference of higher temperatures during the day and lower temperatures early in the morning. The SP object exhibits the greatest difference compared to the control. The maximum temperature difference at the SP object (11.3°C) occurs at 1420 on 31 July 2018 during lower air temperatures. The opposite, lower surface-soil temperatures at the SP object as compared to the control (7.0°C), occurred during lower air temperatures at 1005 on 18 October 2018. For the SM object, the maximum difference compared to the control was 6.06°C at 1230 on 16 September 2018. A temperature difference of (4.09°C) was observed at 1340 on 18 July 2018, which was the coldest day for the period of data analyzed. For the DP, the maximum difference between the object and control was 5.51°C (1200 on 16 July 2018), and the minimum difference was 3.1°C (1345 on 18 July 2018). Like the DM object, the maximum difference between the DP object and control was at 1300 on 16 July 2018 (6.6°C), and the difference at the lowest measured temperature was 3.78°C at 1345 on 18 July 2018.

Figure 21. Temperature difference between objects and control (*red* = SP; *dark blue* = DM; *green* = SM; *turquoise* = DP) for converted temperatures (*left*) and measured temperatures at 5 cm bgs (*right and bottom*). The temperature differences are for after emplacement of objects during (a) 14 July to 15 November 2018 (end of thermal-imagery collection), (b) a higher average air temperature (21.9°C), and (c) a low air temperature (12.3°C).



A large span in temperature difference between the SP object and control can be seen within a day (night to early morning and middle of day to late afternoon). For example, on 20 July, there is about an 11°C difference between 0415 to 1230 (Figure 21*b*). Similar observations are also seen for the other buried objects but with a smaller difference in temperatures. The difference between objects and control decreases during lower temperatures. On 5 October, the difference between early morning (0540) and midday (1240) at the SP object (Figure 21*c*) is less than half (4.5°C) that of the summer example (Figure 21*b*). This corresponds to smaller fluctuations in the diurnal air temperature. In 2018, air temperatures were close to freezing in mid-October, and the first occurrence of below-freezing air temperatures occurred on 18 October. At the control, the ground was frozen from 15 November at a depth of 5 cm bgs (Figure 19*b*); and there was also a smaller, and almost negligible, difference in temperatures between objects and the control.

Because of the limited thermal IR images during lower temperatures, we also evaluated the 5 cm bgs measured soil temperature (right panels in Figures 22 and 23). At this soil depth, the temperature difference exhibits a similar pattern but with greater amplitudes than the thermal IR temperatures. For example, on 20 July, the SP object was about 4°C higher than the control at 5 cm bgs (Figure 23*b*). The same trend is clear at lower temperatures (Figure 23*c*).

Figure 22. Air temperatures and object temperature differences at a soil depth of 5 cm bgs for 14 July 2018 to 22 February 2021.

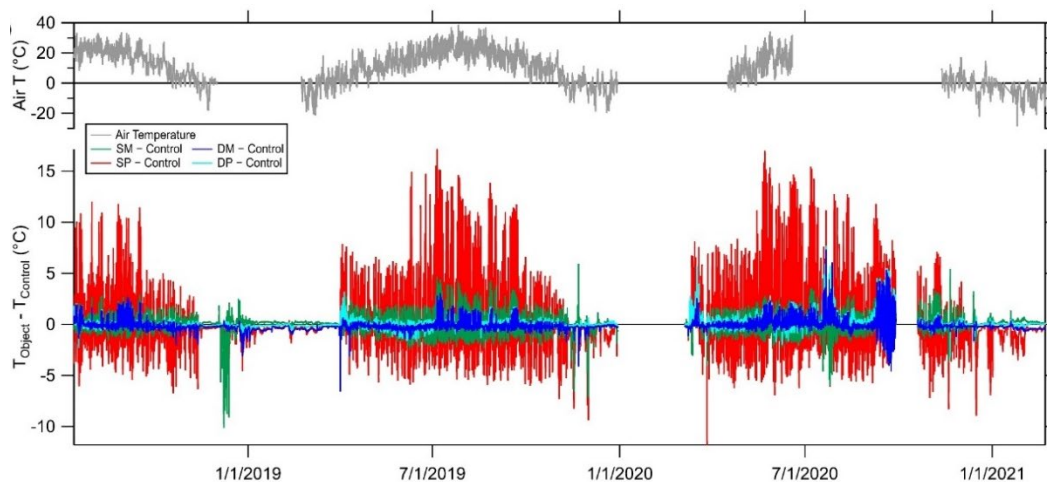
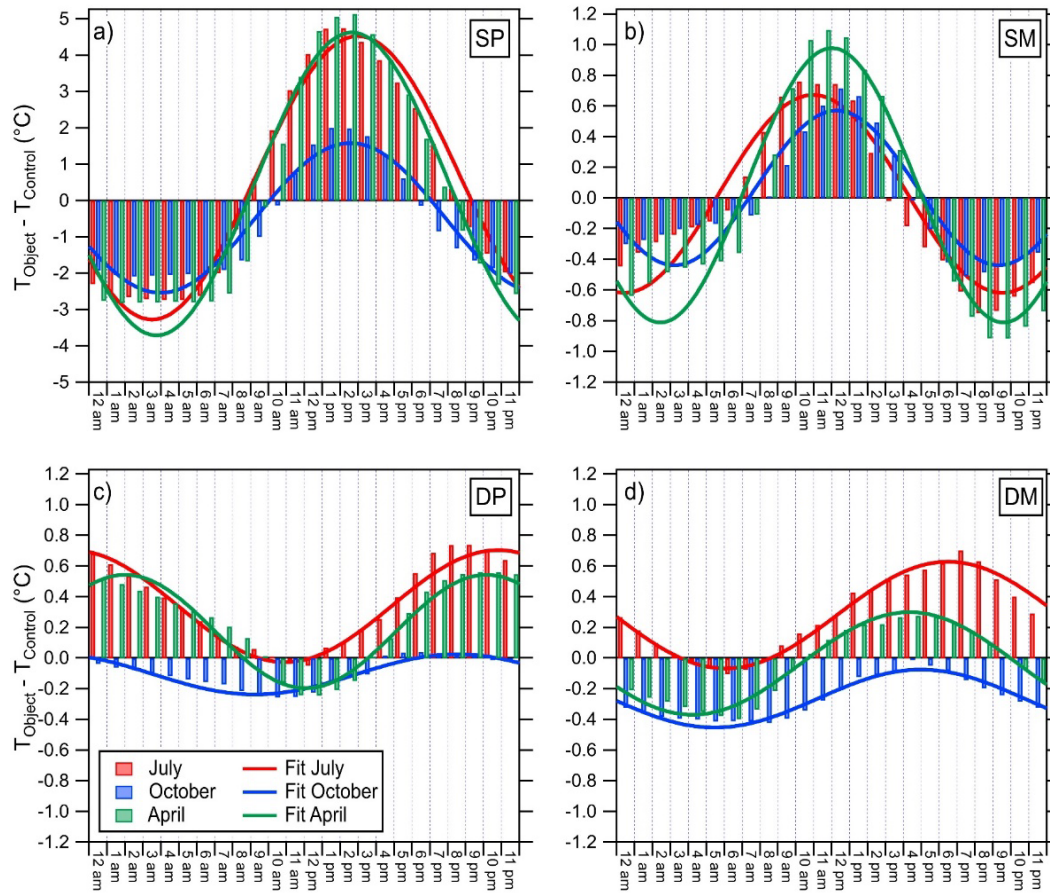


Figure 23. Bar graphs of temperature differences for a high (red bars), low (blue bars), and thawing (green bars) average air temperature at the (a) SP object, (b) SM object, (c) DP object, and (d) DM object. Note the different temperature scales on the y-axis.



Since, at low temperatures, the conversion from radiances to thermal IR temperatures showed potential shift towards even lower temperatures than the actual temperature, we chose to analyze trends in the thermal response using the measured 5 cm bgs soil temperatures. To determine the best time of the day for object detection and how this might be changing depending on air temperatures, we binned the differences between the object and control for each hour of the day (Table 5). We chose days with different air temperatures—16 April to 15 May (6.27°C), 14 to 28 July (21.9°C), and 1 to 14 October (12.3°C)—and from these curves, we also generated sine-wave curves (Table 5). As Figures 22 and 23 show, the SP object exhibits the largest diurnal differences between the object and control. For the SP object, similar amplitudes are shown for the thawing period (April) and warmer period (July). There is a longer period of probability of object detection during the early morning than midday for all temperatures investigated.

Table 5. Sine-wave curves for the difference between the object and the control (t is time).

Object	14 to 28 July 2018	1 to 14 October 2018	15 April to 15 May 2020
SP	$0.63 + 3.90 \times \sin(0.29t - 2.53)$	$-0.48 + 2.06 \times \sin(0.31t - 2.75)$	$0.45 + 4.17 \times \sin(0.30t - 2.65)$
DP	$0.34 + 0.36 \times \sin(0.28t + 1.83)$	$-0.11 + 0.13 \times \sin(0.29t + 2.14)$	$-0.48 + 2.06 \times \sin(0.31t - 2.75)$
SM	$0.03 + 0.64 \times \sin(0.31t - 1.69)$	$0.07 + 0.50 \times \sin(0.36t - 2.69)$	$0.08 + 0.89 \times \sin(0.34t - 2.37)$
DM	$0.28 + 0.35 \times \sin(0.26t - 3.11)$	$-0.26 + 0.19 \times \sin(0.28t - 3.06)$	$-0.04 + 0.33 \times \sin(0.27t - 2.67)$

4.2 Soil-temperature simulations of buried objects at low temperature

Soil thermal modeling of the freezing (3 November to 15 November 2018) and thawing (15 April to 15 May 2020) conditions at the buried objects showed good agreement during higher temperatures (Figure 24). During lower temperatures, some limitations are apparent. For example, during freezing (Figure 24a), it is evident that when lower air temperatures occur (see air temperature in top panel in Figure 24 for 5, 9, 11, 12, and 14 November), the model-simulated soil temperatures were consistently lower than field-measured temperatures. The overestimation of surface-soil-temperature results in soil temperatures too low at depth (see 11 to 14 November at 25 cm bgs depth for SM and DP objects in Figure 24a).

Figure 24. Measured temperature (*black line*) at several depths (5, 25, and 45 cm bgs) during (a) freeze-up (3 November to 14 November 2018), and (b) thaw (16 April to 16 May 2020). Model-simulated temperatures at 5 cm bgs for the boundary condition (*blue line*) and simulated soil temperature (*red line*).

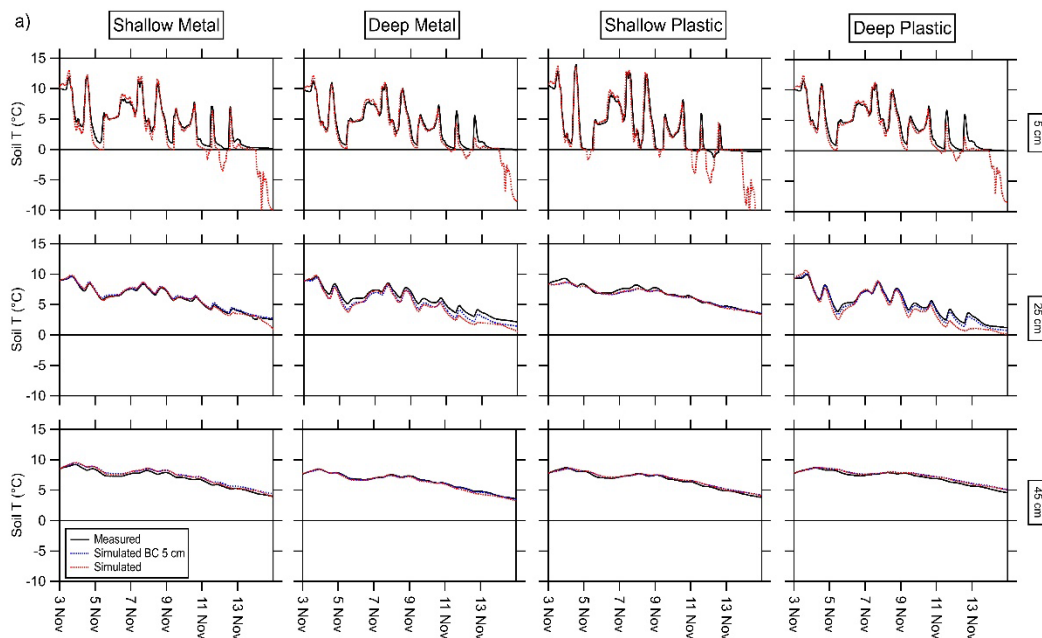
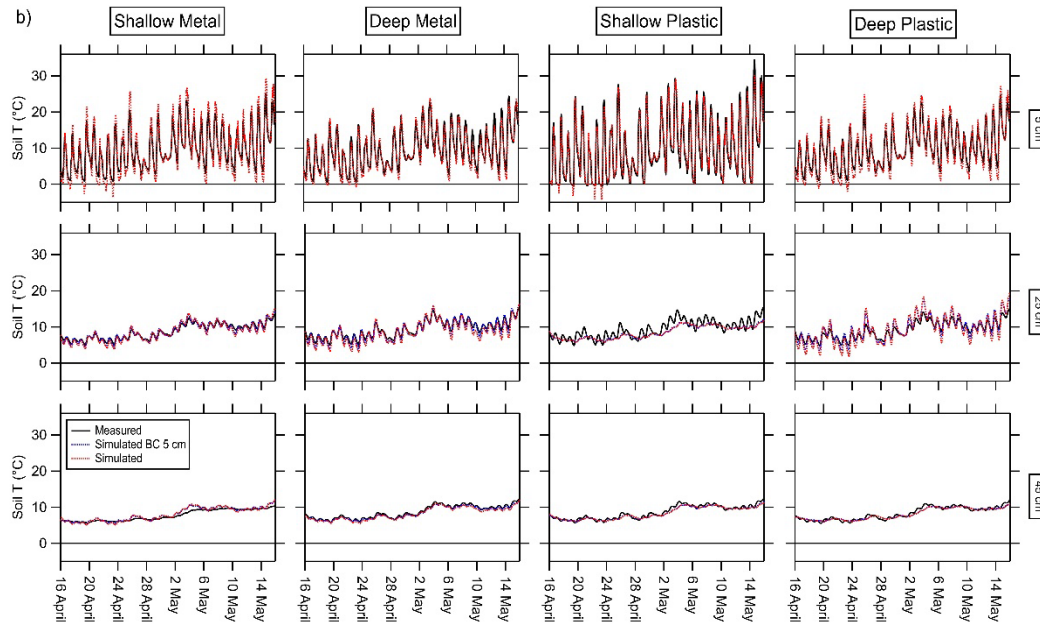


Figure 24 (cont.). Measured temperature (*black line*) at several depths (5, 25, and 45 cm bgs) during (a) freeze-up (3 November to 14 November 2018), and (b) thaw (16 April to 16 May 2020). Model-simulated temperatures at 5 cm bgs for the boundary condition (*blue line*) and simulated soil temperature (*red line*).



4.3 Thermal-modeling conclusions

From our thermal-imagery object-detection analysis, we found that the SP object under all conditions had the greatest probability of detection when compared to the metal object (and deeper objects). Compared to the control, the temperature at the SP object was up to 11°C higher (see 1420 on 31 July 2018). The best time of the day for detection of the SP object at our test plot was between 1300 and 1400 hours (Figure 23a). At night to early morning, the probability of detection had a longer range of detection (9 hours) between 2200 to 0600. The SP object showed a similar probability of detection trend (i.e., time of day) independent of the season investigated (i.e., April to May, July to October). The temperature difference between the other objects compared to the control was low, indicating that the SM and deeper-buried DP and DM objects were more difficult to detect using thermal imagery.

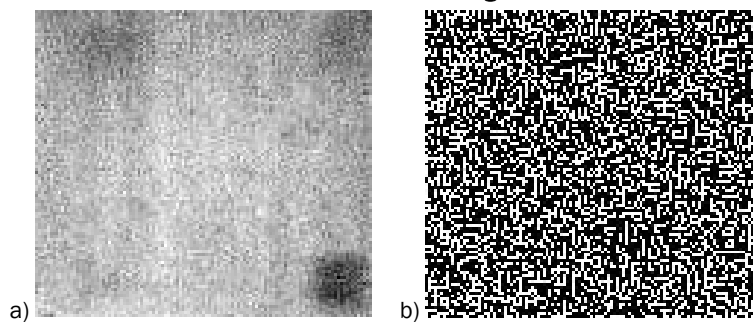
Soil thermal modeling is incredibly sensitive to the soil properties and the forcing applied at the top boundary (i.e., soil surface). During low temperatures (freezing), the model showed a great fit to measured temperatures when the measured temperature at 5 cm bgs was used to force the model. We believe that the misfit in some of the simulations is due to the thermal-imagery conversion from radiance values to temperature during periods

with lower air temperatures. To be able to use the thermal IR imagery as an input to force the model, it is important that this is accurately represented. The model used in this effort did not consider precipitation, change in volumetric water content, or water infiltration. These parameters have a great influence on thermal input and energy balance of the model, so we believe that by applying the thermal IR imagery temperature as the boundary condition, it considers many of these parameters. The model developed in this study showed great agreement with measured temperatures, both at locations with and without buried objects. It was somewhat challenging to obtain a good match between the model-simulated and field-measured soil temperatures when the temperature was low. Despite this discrepancy, our thermal model has the capability to generate synthetic-imagery datasets to obtain a better understanding of the thermal response of buried objects during different environmental conditions.

5 A Computer Vision Approach to Generate Regions of Interest

An objective of our current work is to accurately classify targets from the CRREL test site utilizing a multitude of computer vision (CV) tools. Raw data were extracted from the FLIR thermal IR imagery collected in 2018 (Clausen et al. 2022, 2021; Clausen, Dorvee, et al. 2020) as 240×320 single-channel signed 16-bit (I16) normalized to 8-bit unsigned (U8) integers. The primary technique of focus incorporates Canny edge detection via OpenCV, a programming language developed by Intel for real-time CV. The raw images from the FLIR directory were filtered, transformed, and convolved to reduce noise and contour while preserving edges for effective target detection (Figure 25). The final product is a standalone target-detection prototype designed to run over a directory of images or real-time thermal video capture, outputting a precision and accuracy score for each target. In addition, the final product, or one of its intermediate byproducts or stages, can be used to compliment further statistical approaches more aligned with AI/ML, such as CNN, R-CNN, target-to-clutter ratio neighborhood enrichment test (TCRNet), etc. (McIntosh et al. 2021).

Figure 25. Example of a raw-image contour using (a) a Latin hypercube sampling left-hand-side technique showing an 8-bit unsigned (U8) converted thermal image prior to any transformation and (b) relaxed half-stochastic right-hand-side technique where the contours often dominate the target of interest.



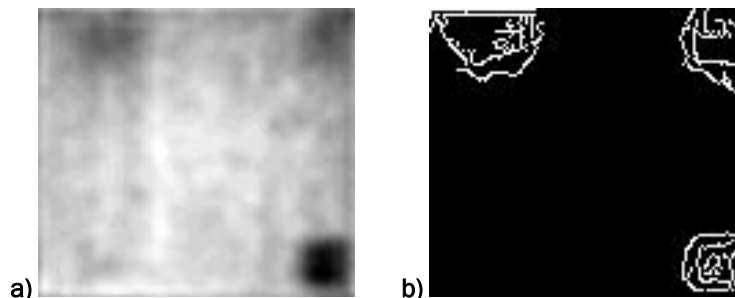
5.1 Computer vision background

CV techniques were developed in the 1960s to assist in developing artificial intelligence, starting with a Massachusetts Institute of Technology PhD thesis by Dr. Lawrence Roberts, considered the father of CV (Roberts 1963). In the early stages of the CV field, the core focus was on three-dimensional machine perception (Szeiski 2010) and with that the ability to

distinguish edges (an ongoing field of study today). The research focus soon evolved into complex and textured topology requiring deconvolution by entering the realm of scale space and Fourier space. With the widespread adoption of ML, feature-based methods have allowed deep learning techniques to be applied to CV frameworks for complex optimization (Sebe et al. 2005).

The following sections describe a prototype CV technique we created that utilizes a multitude of CV techniques inspired from the fields of physics and biology. The prototype discussed in this report is designed to be universal and independent of the raw data conversion and requires no pre-training. Raw FLIR test images were extracted from the CRREL test site in 2018 and uploaded via OpenCV (Bradski 2000), an open-source CV library, and then analyzed primarily with OpenCV, all within the Python programming platform. The final product is a transformed image capable of target recognition with a minimal FAR (Figure 26).

Figure 26. Processed image contour using a left-hand-side algorithm (*left*) showing a U8 converted thermal image after transformation. The right-hand side algorithm (*right*) displays its contour, far simplified from Fig. 25.



5.2 Computer vision methods

The images used in this study were U8 converted data from raw I16 thermal radiance acquired with a FLIR A320 sensor. Because of a multitude of environmental factors, the target of interest's SNR can often be less than 2 (Figure 27), making standard detection techniques unfeasible.

Thus, the CV filtering and transformation techniques are necessary to enhance the SNR for optimal detection to localize the targets for further processing and postanalysis. The edge detection baseline algorithm in its current version analyzes the entire image wholly. Figure 28 displays the stages of the CV algorithm, with each successive stage improving the SNR and enhancing the target detectability.

Figure 27. Raw image of buried targets and associated signal-to-noise ratio.

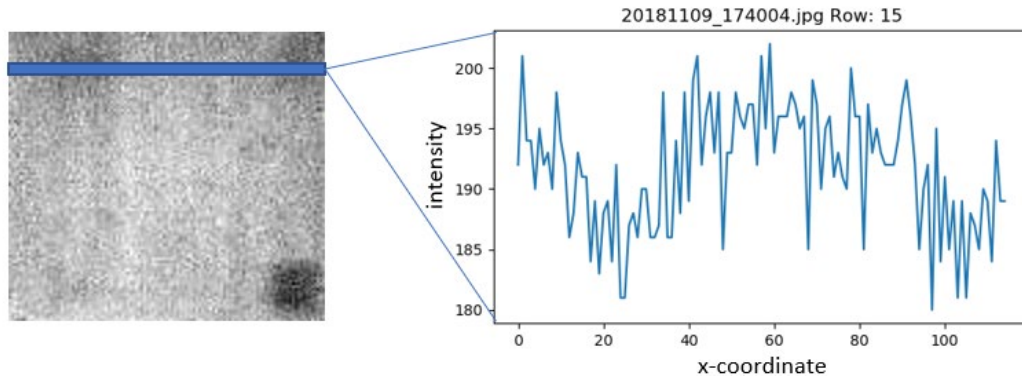
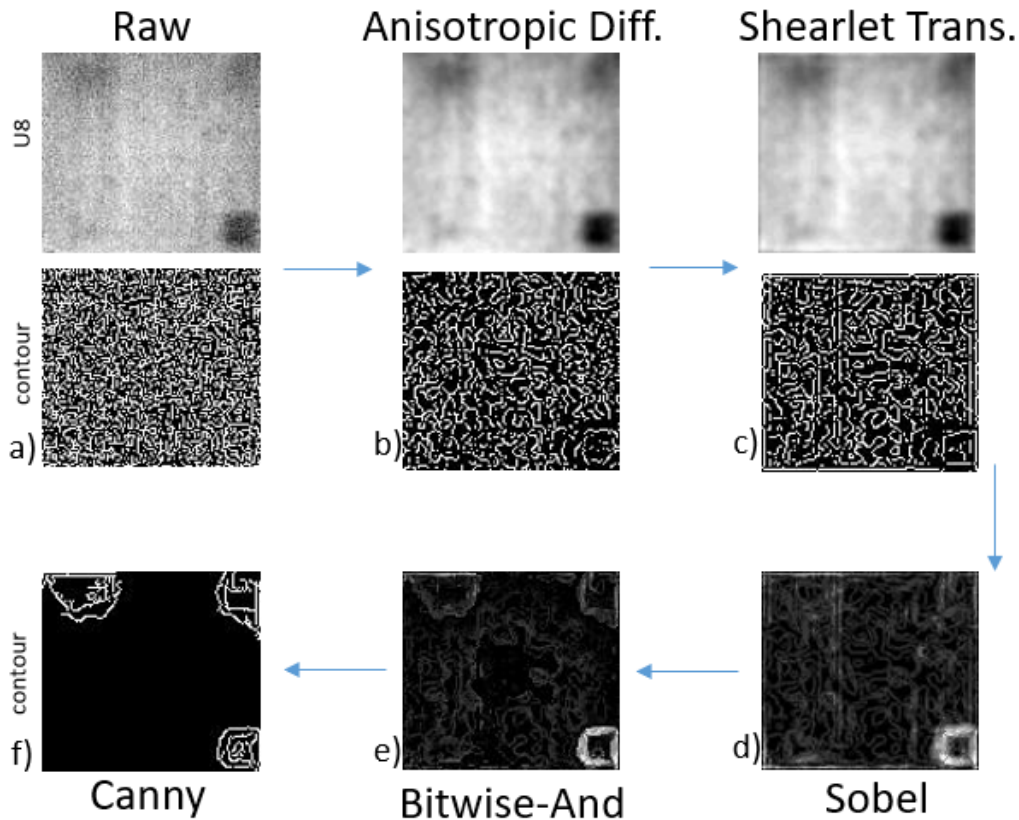
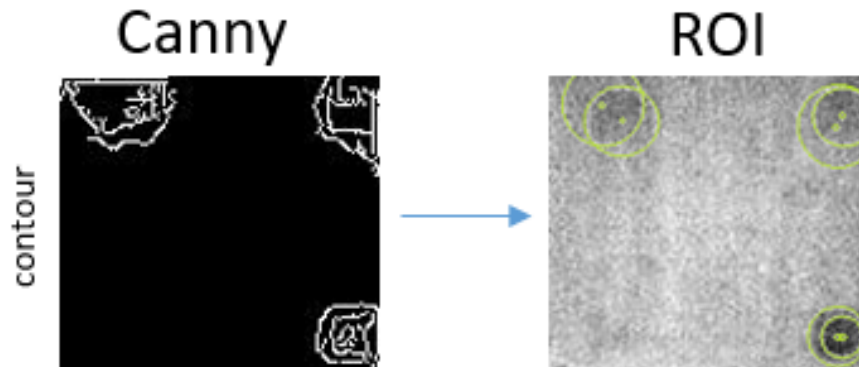


Figure 28. Stages of the baseline edge detection algorithm.



Our technique consisted of first smoothing the raw data (anisotropic diffusion), followed by filtering out the high-frequency salt-and-pepper noise (shearlet transform), amplifying the edges (Sobel operator), and increasing the SNR (bitwise AND operator). Finally, a Canny edge detection operator is applied to help generate the ROIs (Figure 29). The following section discusses the various stages of the baseline algorithm more thoroughly.

Figure 29. Canny contour U8-converted thermal image of Fig. 28 (*left*) with region of interest (ROI) depicted on the *right*.



5.2.1 Baseline method

The smoothing operation chosen for the first stage of the algorithm was anisotropic diffusion, selected to minimize the total energy of the gradient descent equation (Zhu et al. 2016). Perona and Malik (1987) originally introduced this nonlinear and space-variant transformation technique to reduce noise while maintaining the integrity of the edges. The method utilizes a two-dimensional isotropic Gaussian filter on the multistage parameterized smooth images, mirroring a scale-space representation. Within the various levels of the scale space, an impulse function is applied on edge-like regions while smoothed otherwise (in banal regions). The filtering is locally adapted and anisotropic along these lines while isotropic elsewhere, exploiting the global information.

Anisotropic diffusion can be defined in terms of a given gray-scale image, I , whose parameters are a function of the image pixels (x, y) and variance, t , with the following expression:

$$\frac{\partial}{\partial t} I(x, y, t) = \nabla \cdot [c(x, y, t) \nabla I], \quad (8)$$

where c is the diffusion coefficient and controls the rate of diffusion and is generally Gaussian-like. This coefficient has two definitions, described by Perona and Malik (1987) as

$$c(\|I\|) = e^{-\left(\frac{\|\nabla I\|}{K}\right)^2}, \quad (9)$$

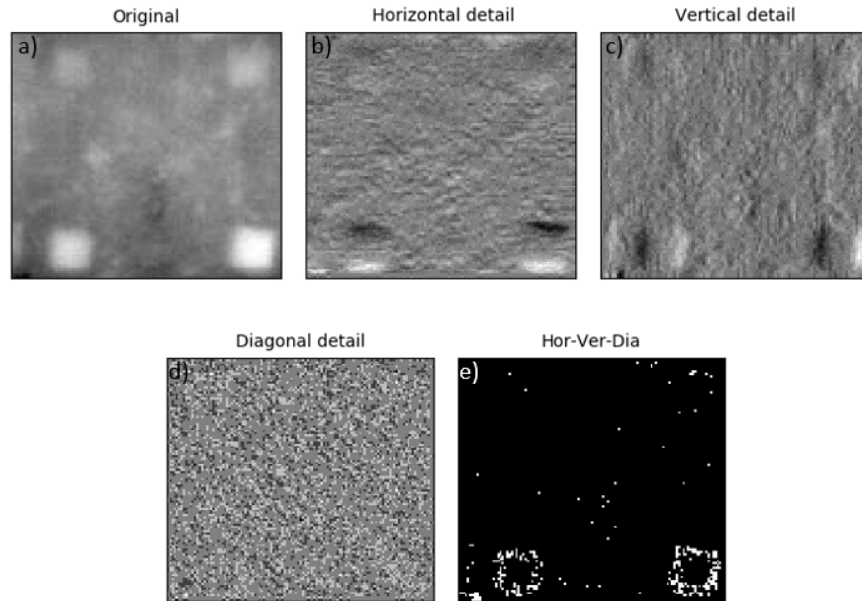
$$(\|I\|) = \frac{1}{1 + \left(\frac{\|\nabla I\|}{K}\right)^2}. \quad (10)$$

Here, K , controls the sensitivity. The specific function used in this work is developed by Kovesi (2000) and then translated to Python by Muldal (2012). We define sensitivity as the impulse function within the scale space being twice the global standard deviation of the image (i.e., $K = 2 \cdot \sigma_{I_0}$). Sensitivity was determined empirically based on a linear regression.

Next, to denoise the byproducts of the smooth image (i.e., removing the salt-and-pepper noise by filtering the high frequency), we choose to enter Fourier space to assist in localizing the singularities. But images are not one-dimensional, and thus we specifically focused on wavelets. One method used to address the problem was discrete wavelength transformations (DWTs). Unlike Fourier transforms, DWTs allows the amplification of desired features in an image by providing local, temporal, and frequency information. The library used for this report is PyWavelets (Lee et al. 2019). This DWT is a convolution between the image with a low-pass and high-pass finite impulse response filter (Figure 30). The detailed coefficients of this transformation have horizontal, vertical, and diagonal components (the approximation coefficient is ignored). We conducted a bitwise OR operation to obtain the final edge-enhanced byproduct (Figure 30e), reminiscent of a Canny edge operation. The detailed coefficients are made up of high- and low-frequency components from the raw image. Detailed features can be extracted to help localize the target of interest.

Alternatively, another wavelet method used in this work is shearlets (Price et al. 2015). Fourier-based shearlet transformations are generalized wavelet transformations with three-dimensional localization. But unlike typical wavelets, shearlets are anisotropic and constructed by parabolic scaling. This directional sensitivity is useful for edge detection.

Figure 30. Discrete wavelet transformations of an (a) original image, (b) horizontal detail, (c) vertical detail, (d) diagonal detail, and (e) final output as a bitwise OR operation.

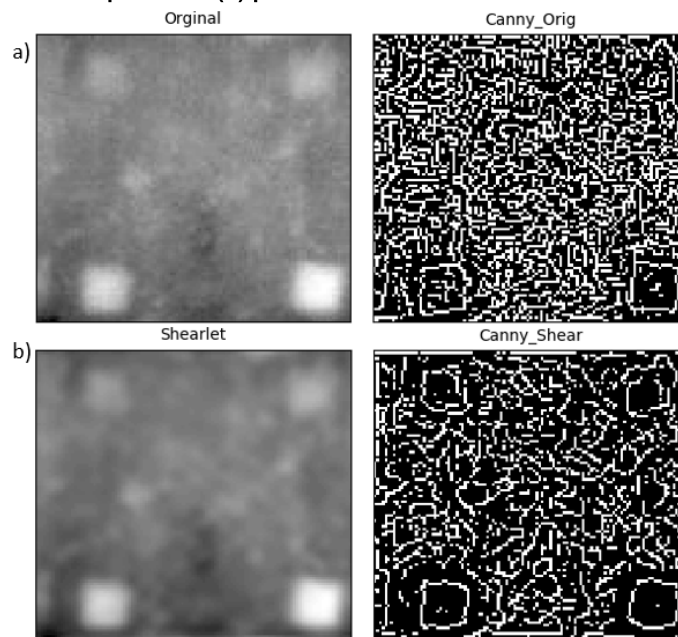


The shearlet library used in the current study is PyShearLab (Loock 2011), currently limited to two-dimensional analysis (gray-scale images). This library is based on ShearLab3D (Kutyniok et al. 2016), developed by Rafael Reisenhofer, and translated to Python by Stefan Loock (Loock 2011). More robust tools exist, but since our raw data are radiant counts, this lack of available dimensionality is more than sufficient. The steps of the algorithm are as follows:

1. **Creating two-dimensional shearlets.** Shearlets are generated from a parabolic scaling, followed by a translation operation and ultimately a shearing operation. The scale of this operation is typically set to 2 if the ROI (105×115 pixels) is omitted from a pyramid upscaling prior to the shearlet operation. The level of shearing (k) is a function of the scale factor (j) through the following relationship $|k| \leq 2^{j/2}$, which for a scale of 2 will equate to a shearing level of 1 for each of the scales. Thus, the generating shearlet is sheared two times in each direction for each cone, centered in the time domain. The shearlet for this scale is a $105 \times 105 \times 17$ array in the frequency domain.
2. **Obtaining Coefficients.** The coefficients are a pointwise multiplication between the shearlets and the raw data in the frequency domain (equivalent to a convolution in the time domain), with a depth determined by the shearlets.

3. **Wavelet Thresholding.** The absolute value of the coefficients is filtered where any value that falls below a specified threshold is set to zero. The threshold value is increased linearly with the raw image's mean standard deviation ($T = \sigma_{I_0}/25$). This step is for denoising the shearlets prior to reconstruction.
4. **Reconstruction.** The two-dimensional data is reconstructed back into the original shape. Figure 31 shows a comparison between the image's contour (via Canny edge detection) pre- and post-transform.

Figure 31. A comparison between the image's contour (a) pre- and (b) post-shearlet transformation.



The shearlet thus aids in minimizing high-frequency noise responsible for speckling effects and, combined with an anisotropic diffusion operation, creates a final product with decipherable edges (Figure 31b).

Next, we want to focus on increasing the SNR of the filtered image. Since edge-like geometries are now unobscured, a series of convolutions can be applied to dispartate the noise floor from potential targets. The primary function in this stage is the isotropic Sobel operator. It computes an approximation of the first-order gradient of an image's intensity function. For a 3×3 kernel, if we define the image as I , and the approximated horizontal and vertical derivative as G_x and G_y , respectively, then that operator is simply defined as

$$G = \sqrt{G_x + G_y}, \quad (11)$$

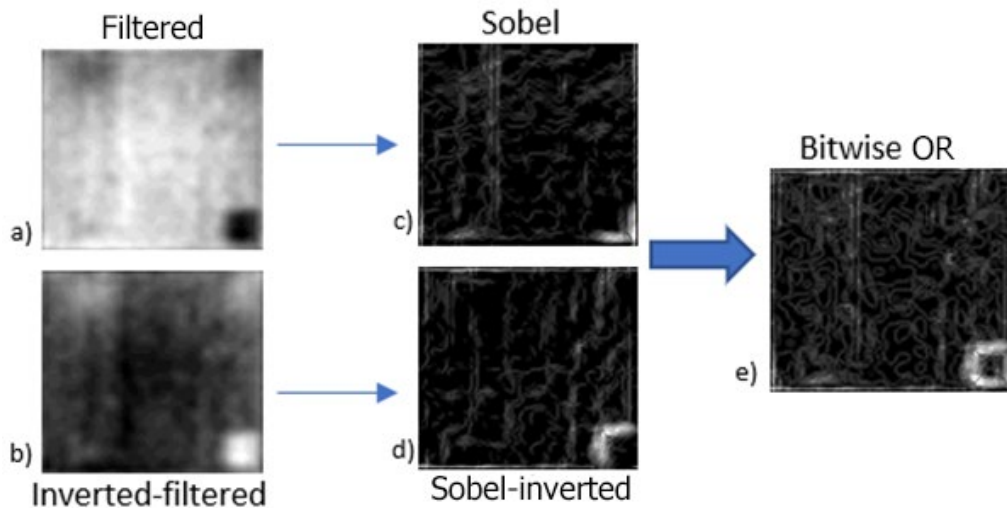
where

$$G_x = \begin{bmatrix} +1 & 0 & -1 \\ +2 & 0 & -2 \\ +1 & 0 & -1 \end{bmatrix} * I, \quad (12)$$

$$G_y = \begin{bmatrix} +1 & +2 & +1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} * I. \quad (13)$$

The Sobel operation, by definition, can localize edges due to a jump in pixel intensity when a gradient is at an extrema due to edge-like topology. Specifically, in our work, we invert the filtered image and perform the Sobel operation on both the negated and regular filtered images due to the varying directional sensitivity and combine the byproducts with a bitwise OR operation. Figure 32 shows the phases of the Sobel stage of the baseline algorithm.

Figure 32. Sobel operation of the baseline algorithm for (a) filtered thermal infrared (IR), (b) inverted-filtered, (c) Sobel-transformed, (d) Sobel-inverted, and (e) bitwise OR images.



Bitwise operations were conducted often throughout the baseline algorithm to enhance edge-like candidates and to calculate the per-element bitwise conjunction or disjunction of two images of the same size and depth, depending on the logical argument executed. Bitwise operations are arithmetic operators (i.e., $\wedge$, $\vee$, $\otimes$, $\&$, and $\neg$) and are powerful tools in the

development of synthetic imagery. Our analysis is performed once again with a bitwise AND operator between the Sobel's byproduct (Figure 32e) and the post-shearlet image (Figure 32a) to generate the image earlier observed in Figure 28.

Finally, the familiar Canny edge detection function applied is a multistage algorithm that first reduces the noise, then localizes the intensity gradients and nonmaximal suppression, and concludes with hysteresis thresholding. The noise reduction is usually conducted by convolving a Gaussian kernel with the image, which in our case with the baseline algorithm used corresponds to a 5×5 kernel. Localizing the edge gradient, G , for each pixel is conducted similarly to the Sobel:

$$G = \sqrt{G_x^2 + G_y^2}, \quad (14)$$

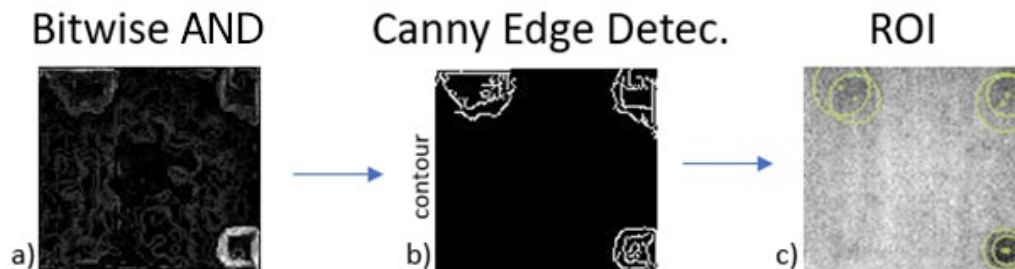
$$\Theta = \tan^{-1} \left(\frac{G_y}{G_x} \right). \quad (15)$$

With the gradient's magnitude and direction known, nonlocal maximums are suppressed based on their orientation with the gradient. The byproduct will be a binary image to which we can set a minimum and maximum value to filter out unwanted intensity gradients. Calibrating this threshold setting is an ongoing pursuit to improve the CV baseline algorithm. The lower threshold is usually set to zero, while the upper equates to

$$T_U = 5 * \sigma_S,$$

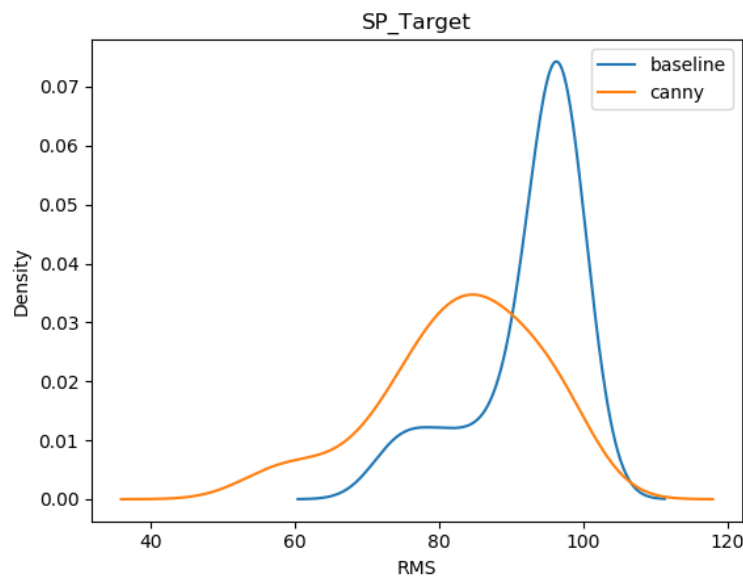
where σ_S is the global standard deviation of the post-bitwise AND image (Figure 28e; Figure 33a).

Figure 33. Canny edge detection process after (a) the bitwise AND operation, (b) application of the Canny edge detection operator, and (c) production of the ROI to which potential targets can be localized and output to a machine learning algorithm for further postprocessing.



The binary image in Figure 33b can now be analyzed to detect targets of interest based on its topology. One method for this feature extraction is looking at the linear binary byproducts of the Canny operation with the use of the probabilistic Hough transform (Matas et al. 2000), commonly utilized to detect straight lines. The threshold parameter for the minimum number of intersections needed to declare a line in the Hough transform is defined in this baseline as proportional to the mean pixel intensity of the Canny byproduct. The lines must surpass a minimum length, defined here in terms of the Canny kernel value of 5, with a maximum allowed gap between points set at double the kernel, which is the threshold value of 10. The coordinates of the lines are recorded to allow the possibility of creating an ROI for postprocessing (Figure 33c). Figure 34 displays a comparison of the ROI generation between the baseline and the standard Canny edge detection algorithm for the SP target in the CRREL test plot.

Figure 34. Probability density function comparison for a baseline versus Canny curve for the SP object.

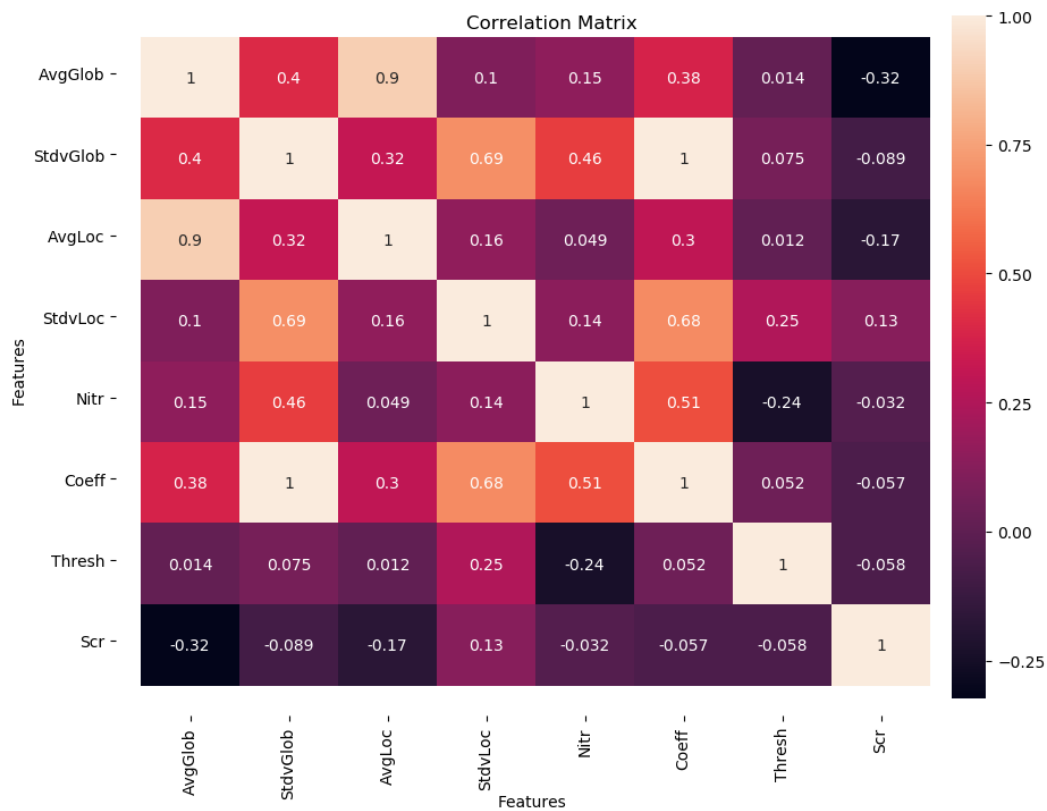


The probability density function shown in Figure 34 is generated with a Gaussian kernel by using a kernel density estimate. The root-mean-square (RMS) is normalized to 100 and is a measurement of the ROI's accuracy to the actual target's known location. It is evident in Figure 34 that the presented steps described above in developing the CV baseline perform substantially better (blue line) in comparison to the Canny edge detection alone (orange line). Values less than 85 are considered false targets and left unfiltered for further postprocessing and training.

5.2.2 Optimization of the baseline

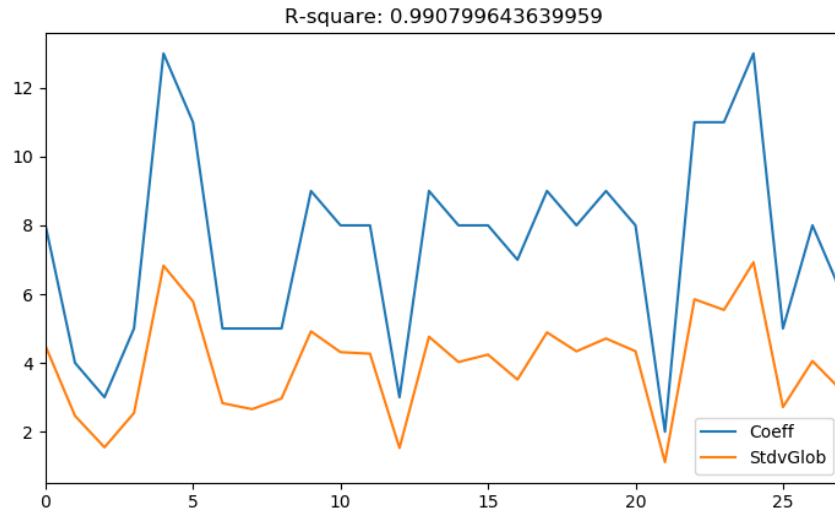
The function parameters from Section 5.2.1 were empirically set. For example, the sensitivity for the diffusion coefficient from the anisotropic diffusion transformation was $K = 2 \cdot \sigma_{I_0}$, and similarly the upper threshold on the Canny edge detection was defined as $T_U = 5 \cdot \sigma_S$. Knowing where the target of interest is in this exercise, multiple permutations of these parameters can thus be tested to uncover which configurations will output the highest score (or RMS). All permutations between the parameters were tested with nested loops to couple the global (Glob) and local (Loc) information from each sample that helps generate the highest score (Figure 35). These relationships aid in developing parameters that are a function of global and local information.

Figure 35. Correlation matrix for the baseline curve.



The comparison between the function's parameters and global and local information is conducted with use of a correlation matrix as depicted in Figure 35. For example, a strong correlation is observed between Coeff and StdvGlob, the diffusion coefficient and global standard deviation, respectively. Figure 36 shows these two values plotted to quantify their regression.

Figure 36. Parameter optimization.



In Figure 36, the coefficient of determination, or R^2 , between both parameters is close to 1 for the diffusion coefficient stated earlier for the equation

$$K = 2\sigma_{I_0}.$$

This relationship was developed by conducting nested loops between the diffusion coefficient and the global standard deviation to minimize the R^2 output. Similar methods are conducted to further optimize the other parameters to refine the baseline until ultimately enabling localization of unknown targets.

5.2.3 Computer vision discussion

The CV prototype introduced is effective at finding targets that are semi-obscured to the naked eye. When the SNR is approximately 1, the algorithm has a higher failure rate. This is evident in Figure 34 when looking at the baseline's probability density function (blue) with a secondary peak centered at about 75, outside of the satisfactory range of 85. This secondary peak is a byproduct of an increase in the soil's volumetric water content or lack of thermal stimulant (no solar input). Alternative normalization techniques on the raw data will need to be explored to minimize the noise floor and improve performance. We also need to assess convolution between these various normalizations to increase depth by converting the data into an RGB scale. Additionally, implementing environmental variables to aid in optimizing the baseline's parameters could further reduce the R^2 value observed in Figure 36 since current indicators are limited only to the raw data's global standard deviation (Figure 35). Initial assessments on

incoming solar radiation, relative humidity, and the volumetric water content of the soil have displayed promising correlations to the function's parameters.

6 Automatic Object Recognition from a Machine Learning Approach

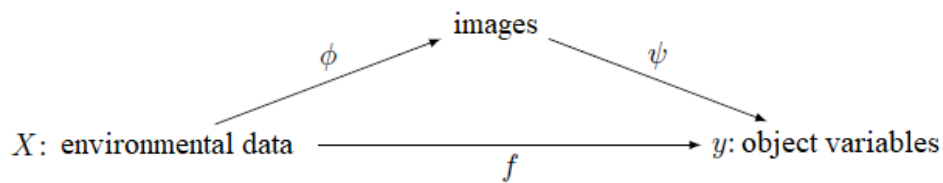
The work in this section has two goals: (1) to understand how environmental conditions impact the ability to detect buried objects using thermal IR imaging and (2) utilizing environmental conditions to inform the classification of buried objects using an ML approach. Clausen, Dorvee, et al. (2020); Clausen, Musty, et al. (2020); Clausen et al. (2021); and Clausen et al. (2022) have shown that the environmental and meteorological conditions at the time of the thermal imaging can affect the ability to detect buried objects. For example, precipitation events, which increase the volumetric water content of the soil, mask the object within the thermal image. Because of these known effects on object detection, it is desirable to incorporate the environmental phenomenological information into object-detection algorithms. This leads to the first objective of this work, which is captured in the schematic diagram shown in Figure 37.

Ideally, we would like to understand how the environmental conditions directly impact the thermal signature of buried objects observed in thermal images. In Figure 37, the function ϕ represents this relationship, where ϕ has an input of the environmental conditions, X , and outputs a predicted thermal signature for buried objects. However, this is too broad of a question to study. To simplify the problem, we introduce a thermal IR image proxy, which we call the object variables, denoted by y . In Figure 37, the function ψ represents this mapping, meaning ψ takes in a thermal image and the output is a scalar-valued object variable, y . Section 6.2 introduces the object variables used in this report. Then, to understand the impact environmental conditions have on a thermal IR image containing a buried object, we study the relationship between the environmental variables and the object variables. This is represented by the function f in Figure 37, whose inputs are the environmental variables, X , at the time the image was captured; and the function f predicts the corresponding object variable, y . This relationship is studied in Section 6.3.

The function, f , that maps the environmental variables to the object variables is nonlinear, and we use ML to model this relationship. This is a regression ML task in which the algorithm learns the nonlinear relationship between the environmental conditions and the object variables. We use a feature-importance measure paired with the ML algorithm to assess which

environmental input features are the most influential in the prediction of the object variable. The feature importance allows us to quantify which environmental variables impact the visibility of buried objects in thermal imaging. Lastly, we use the knowledge gained by studying the nonlinear function, f , for the second main objective of this work. Meaning, we use the environmental variables that impact buried-object visibility the most to inform the classification ROIs produced by the CV baseline algorithm discussed in Section 5. The result is an environmentally informed classification algorithm that combines the important environmental variables with the ROIs to classify the ROIs more accurately as containing a buried object or not.

Figure 37. A representation of the main objectives for incorporating the environmental phenomenology into thermal IR image analysis for target identification.



The results in Sections 6.2 and 6.3 are an extension of the work presented in Section 6 of the Phase III technical report (Clausen et al. 2022). Clausen et al. (2022) defines a simple binary classifier, which compares the mean value of object pixels and background pixels, and the performance of the classifier is quantified using the area under the receiver operating characteristic (ROC) curve (AUC). Since the simple binary classifier is probabilistic, an ensemble average of the AUC measure is used as the object variable. However, it is known that the statistic used to measure the contrast metric greatly affects the performance of detection algorithms, and t-test statistics can provide a more robust measure of contrast between pixels (Schachter 2013). Thus, it is important to explore appropriate choices for the object variable. In this work, we explore using variations of both the SNR and the t-test as candidate object variables (Schachter 2013, 2020).

Clausen et al. (2022) described the first attempt at modeling the nonlinear function, f , in Figure 37. The object variable, y , was taken to be the average AUC measure; and the environmental variable, X , was taken to be the full set of environmental measurements. Associated with each object variable was a set of nearly 300 environmental measurements collected from the buried sensors within the test plot and the meteorological station. Clausen

et al. (2022) used PCA to obtain a lower-dimensional representation of the environmental variables by projecting the 300-dimensional vector onto the first nine principal components to obtain a 9-dimensional representation. The lower-dimensional projection of the environmental data was analyzed with the AUC object variables to begin to identify relationships between the AUC value and the corresponding environmental conditions. The lower the AUC value, the less likely the object is visible within the image. In Clausen et al. (2022), the ML algorithm XGBoost (Chen and Guestrin 2016) was used to further study the nonlinear function f mapping the environmental variables to the object variables (AUC). The XGBoost algorithm was paired with linear Shapley analysis, which helps identify the environmental features that play the biggest role in the AUC object variable prediction.

To aid in the interpretation of the important environmental features obtained from XGBoost and the Shapley analysis, the full set of environmental variables were used. Linear Shapley analysis (Štrumbelj and Kononenko 2014) is an algorithm that approximates feature importance by decomposing the predicted object variable into a baseline effect and a sum of responses from each environmental variable. The approximated feature-importance measure is given by the response to the feature in the linear Shapley analysis. The application of XGBoost with linear Shapley analysis yielded incoming solar radiation and heat flux as the two most important environmental factors in predicting the AUC values for a given image. In Clausen et al. (2022), the approach used to model f suffered from overfitting, and the feature importance was determined by an estimation algorithm, which is not necessarily the most accurate representation of feature importance.

In this work, we improve upon the modeling and analysis of the nonlinear function f . We use the new object variables defined by t-test statistics and the SNR, which we also called contrast metrics. In Section 6.1, we discuss a subset of environmental variables used as the input for the model. The subset of environmental variables is selected such that it uses environmental and meteorological features that can be easily obtained or approximated from outside sources, while capturing the relevant environmental conditions that impact buried-object visibility using thermal IR. First, we interpret the subset of environmental variables as independent and identically distributed (iid), meaning, we are assuming that only the environmental conditions at the time of imaging impact the thermal signature of the buried objects. Second, we explore the inherent time series nature of the

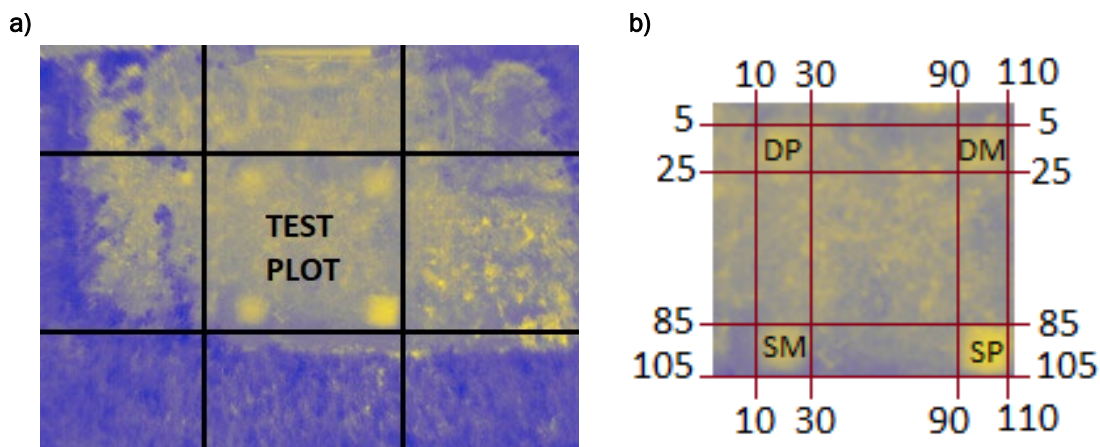
environmental data by considering sequential features calculated using the tsfresh software (Christ et al. 2021). Expanding on the work in Clausen et al. (2022), we implemented a new ML algorithm using a deep neural network called TabNet, which has built-in interpretability, and the architecture is specifically designed for processing and learning tabular data (Arik and Pfister 2020; Dreamquark-AI 2020). Variations of gradient-boosted ML algorithms have been the benchmark for processing tabular data (Chen and Guestrin 2016); however, the newly introduced TabNet architecture has been shown to outperform gradient-boosted machines in learning tasks (Arik and Pfister 2020). We compared the performance of the gradient-boosted trees algorithm to the TabNet algorithm for the task of modeling the relationship between the environmental variables and the new object variables. The TabNet algorithm differs from gradient-boosted trees algorithms by using sequential attention to choose which input features should be used in a given decision step. Another benefit of the TabNet algorithm is that it contains built-in feature importance thanks to the sequential attention framework, and this can be used to understand which environmental variables played the biggest role in producing the prediction without employing an approximate method like linear Shapley analysis.

Lastly, we attempted to incorporate the environmental variables into an automatic object-recognition algorithm. One approach is to attempt to predict the hyperparameters governing the object recognition in the CV baseline algorithm discussed in Section 5. The second is integrating the tabular environmental data with the ROIs produced by the CV baseline algorithm and processing this data through a deep-learning classifier to determine whether an object is present in the ROI. Lastly, we assessed the performance of the CV baseline algorithm by analyzing the contrast-metric distributions for when a given object is detected.

The present report uses thermal IR images from a May to November 2018 timeframe, collected at the CRREL test plot in two different phases. For the Phase II dataset, the soil in the test plot was homogenized, and thermal imagery was collected prior to object emplacement on 11 July 2018 (Clausen, Dorvee et al. 2020; Clausen et al. 2021). Then, four objects were emplaced at the test plot: SP and SM each with the top buried at a depth of 5 cm bgs and DP and DM objects each with the top buried at a depth of 25 cm bgs. The objects were 40 × 40 × 20 cm boxes made of either metal (aluminum) or plastic (HDPE) and filled with nitrogen fertilizer. A variety of temperature and moisture sensors are buried within the CRREL test

plot (Clausen et al. 2021). During the Phase II data collection, the test plot was kept free of vegetation. Figure 38 shows a sample thermal image of the entire field of view and the corresponding cropped image of the test plot highlighting the pixel locations of the buried objects.

Figure 38. Sample thermal infrared image from 9 September 2018 taken at 1420 for (a) the entire field of view taken by the forward-looking IR (FLIR) cameras with the test plot highlighted in the center of the image and (b) a cropped thermal infrared image of the test plot where the four buried objects (SP, SM, DP, and DM) are labeled with corresponding pixels in the cropped image.



6.1 Environmental and meteorological data

In the test plot, CS655 sensors are used to measure the temperature, electric conductivity, and moisture of the soil. The sensors are buried at various depths (5, 15, and 35 cm bgs) and various locations throughout the test plot. Other environmental variables tracked for the study include heat flux, heat-plate temperatures (surface temperatures), and incoming and reflected solar radiation. Weather conditions are tracked using a meteorological station installed at the CRREL test plot; and the measurements include average air temperature, average pressure, 24-hour rain accumulation total (millimeters), relative humidity, average wind speed, and average wind directions. The weather data is further supplemented with data collected from the nearby Lebanon, New Hampshire, airport; and this includes cloud cover, pressure, 1- and 3-hour rain totals, 1- and 3-hour snow total, and the minimum and maximum temperature for the day. Time of day is tracked in seconds. See Clausen et al. (2021) and (2022) for more details about the sensors used and their placement within the test plot.

6.1.1 iid environmental variables

We chose a subset of the environmental variables that are easily approximated by accessing local meteorological and soil data. The focus was on the following 10 environmental variables:

- average air temperature (degrees Celsius)
- average pressure (millibars)
- 15-minute rain totals (millimeters)
- the average incoming (shortwave) solar radiation (watts per square meter)
- the average reflected (shortwave) solar radiation (watts per square meter)
- average soil moisture (volumetric water content) at 15 cm depth (percent)
- average wind direction (angle)
- average wind speed (meters per second)
- average relative humidity (percent)
- average snow depth (millimeters)

The sensors and the meteorological station at the CRREL test plot record the sensor values every 15 minutes, while the images are taken on 5-minute intervals. A simple approximation of the 15-minute environmental data was performed to obtain 5-minute resolution; and the result of this data forms the iid environmental data, which is different compared to the snapshot data used in the Phase III technical report (Clausen et al. 2022).

For the environmental data, besides the rain total at 15-minute intervals, we computed a simple average to form the 5-minute-resolution data. For example, on 1 July 2018 at 0900, the air temperature was 25.98°C; and at 0915, it increased to 26.65°C. To obtain the approximate 5-minute-resolution data for 0900, 0905, and 0910, the temperature measurements at 0900 and 0915 were averaged to yield a value of 26.3°C for the 5-minute data. We used this approximation process to obtain 5-minute-resolution environmental data for all the environmental variables, except the rain total over 15 minutes. For the average soil moisture variable, the average 15-minute resolution is first obtained by averaging the measurements of the 13 different sensors buried at 15 cm bgs in the test plot. Once this averaging process is completed, the 5-minute-resolution approximation is computed in the same manner. The Phase III technical report (Clausen et al. 2022) found that the soil moisture content at a depth of 15 cm bgs was the

most important feature in predicting an object variable when compared to the sensors buried at 25 and 35 cm bgs. For the rain total over 15 minutes, we obtained the approximate 5-minute-resolution data by simply dividing the 15-minute-resolution data by three and using that result for the 5-minute approximation. Thus, for 25 June 2018 at 0000, 0005, and 0010, an approximate measurement of 0.0846 mm of rain is used for each 5-minute interval to preserve the 15-minute rain totals.

6.1.2 Sequential environmental variables

Another way to view the environmental variables is by taking advantage of the time series nature of the data. By using the software package `tsfresh`, various sequential features can be extracted from the environmental time series data. To do so, we create 6-hour time series for each timestamp such that each time series incorporates the trends of the 6 hours leading up to the timestamp. Meaning, for an image captured at 0815 on 28 September 2018, the 6-hour time series associated with the timestamp spans from 0215 to 0815, and we formulate 6-hour time series for each of the 10 iid environmental variables. Then the `tsfresh` software is utilized to extract sequential features for these 6-hour time series associated with each timestamp, where the sequential features capture the characteristics of the time series. Using the `tsfresh` package for each environmental time series associated with an individual timestamp, 79 different sequential features are extractable. The computed sequential features vary from simple statistical calculations, like the mean, absolute maximum/minimum, and standard deviation, and techniques like linear regression to more complex approximations, such as the Fourier entropy, absolute energy, and Fourier approximation. See Christ et al. (2018, 2021) for more details on the varieties of extracted features. By applying `tsfresh` to the environmental time series formulated for each timestamp, we create a new set of sequential environmental features that contains up to 79 features for each iid environmental feature for each timestamp. Meaning, we increase the dimension from 10 iid environmental features per timestamp to approximately 790 sequential environmental features per timestamp. The sequential features computed for each timestamp contain the history of environmental conditions for the 6 hours prior to imaging. The increased data dimension does come at a cost of increased complexity, and this trade-off is investigated following analysis of the nonlinear prediction of the contrast metrics in the next section.

6.2 Object variables and contrast metrics

One improvement on the Phase III approach (Clausen et al. 2022) in this work is the use of object variables. In Phase III, a simple binary classifier gave the output of an AUC measure for each image. This classification method is probabilistic and requires running the classifier multiple times to obtain an average AUC for each image. Because each object image contains four objects, two deep, two shallow, each of which is either metal or plastic, this resulted in nine object variables per image. As noted in Schachter (2013), the choice of object variable can greatly affect the chosen algorithms used to process the relevant image data, which is a motivating factor for investigating alternate object variables than what was discussed in the Phase III technical report (Clausen et al. 2022). In the current report, we improve upon the definition of the object variable by using contrast measures based on the mean value, standard deviation, etc. of the image. The contrast measures depend on defining both object and background ROIs. For our purposes, the background and object ROIs in each image are known, and the computed measures that highlight the difference between the background and object pixels are collectively called contrast metrics. The first of these contrast metrics is known as the Michelson contrast metric (Michelson 1927), C_m which is commonly used in CV to measure visibility of contrasting features in images, such as light and dark areas of an image. The Michelson contrast metric is defined as follows:

$$M_1 = C_m = \frac{\mu_t - \mu_b}{\mu_t + \mu_b}, \quad (16)$$

where

- C_m = Michelson contrast metric;
- μ_t = the mean value of object ROI, which can be as small as one pixel; and
- μ_b = the mean value of the background close to the object, which we call the local AOI, which can be as small as one pixel.

The Michelson contrast can be used on a pixel-by-pixel basis to produce a so-called Michelson image, provided the background ROI is defined as one or more pixel and μ_t is taken to be each pixel value throughout the image. If a specific ROI is defined, then the Michelson contrast is a number, not an image, such that $C_m \in [-1, 1]$. The closer C_m is to zero, the less visible

the object is compared to the background. The numerator of the Michelson contrast metric, $\mu_t - \mu_b$, is also called the signal of the object.

The Michelson contrast can be adjusted to account for the minimum value within the region of interest that contains both the object and its local background. This minimum value is often called the pedestal common to the object and background pixels. The relevant spatial information in the scene rides on top of this pedestal in the image, thus scaling the denominator of the Michelson contrast metric, C_m , by the image pedestal can help enhance the measured contrast between the background and object AOIs. This results in the adjusted Michelson contrast metric, C_{ma} , defined as follows:

$$M_2 = C_{ma} = \frac{\mu_t - \mu_b}{\mu_t + \mu_b - 2 * \min}, \quad (17)$$

where

$\mu_t - \mu_b$ = the signal and
 $\min$ = the minimum value within the ROI containing the object and the local background.

Like the Michelson contrast metric, the adjusted Michelson contrast can be used to produce an adjusted Michelson contrast image. If the defined object and background ROI are greater than one pixel, then C_{ma} in Equation 17 is a number between -1 and 1 .

Next, a contrast metric that is defined using the RSS of different statistics computed for the image is considered (Schachter 2013). The metric, C_{RSS} , is defined as follows:

$$M_3 = C_{RSS} = \frac{\sqrt{(\mu_t - \mu_b)^2 + \sigma_t^2}}{\mu_t + \mu_b}, \quad (18)$$

where

σ_t = the spatial standard deviation of the object, which must consist of multiple pixels, and
 μ_t and μ_b = the same as in the M_1 and M_2 .

The numerator is considered the magnitude of noise and is computed using the first- and second-order statistics of the object and background. The

RSS contrast metric reduces to the Michelson contrast metric in the case when the object has no variance ($\sigma_{t^2} = 0$). Note, that the RSS contrast metric does not contain information about the background variance in the image, so there is no comparison of the object variance to the background variance. To compute the RSS contrast metric, the object ROI is larger than one pixel to compute the object variance. An RSS contrast image can be produced by applying the RSS contrast metric throughout the image by using a so-called sliding window, for example a window that is 3×3 pixels, to compute C_{RSS} at each pixel of the image. The numerator in C_{RSS} will never be less than the spatial standard deviation of the object, even when the average object and average background are the same, which is the scenario in which the Michelson contrast metric goes to zero. The RSS contrast metric takes on values in the interval $[0, \infty)$.

The next considered contrast metric uses an RSS computed with the object and background spatial variances:

$$M_4 = T_2 = \frac{\mu_t - \mu_b}{\sqrt{\sigma_t^2 + \sigma_b^2}}, \quad (19)$$

where

σ_b = the spatial standard deviation of the local background surrounding the object, which must contain multiple pixels, and

μ_t, μ_b , and σ_b = the same as above.

The contrast metric, T_2 , is a simplified t-test statistic, which is the two-sided test (Schachter 2013). The above contrast metric is equivalent to a SNR variation where the noise is computed using the RSS of the object and background spatial noise or variance. Note, that if $\sigma_t^2 \approx \sigma_b^2$, which is the scenario in which the image is limited by camera noise or scene noise and is approximately constant in the entire image, then $T_2 \approx$ a SNR, where the noise is given by the background noise.

The next two contrast metrics are simple SNR expressions either computed with the noise from the entire image, σ_i , or the noise from only the background (Schachter 2013):

$$M_5 = T_{10} = \frac{\mu_t - \mu_b}{\sigma_i}, \quad (20)$$

$$M_6 = T_{10a} = \frac{\mu_t - \mu_b}{\sigma_b}. \quad (21)$$

Another t-test that has been shown to perform well on FLIR images (Schachter 2013) is given by

$$M_7 = T_{14} = \frac{\mu_t - \mu_b}{\sqrt{\sigma_t^2 + \sigma_i^2}}, \quad (22)$$

which is like M_4 (or T_2) with the difference that the denominator RSS is computed with the noise of the entire image rather than the noise of just the background. The contrast metrics M_4 through M_7 can take on any real number value.

The remainder of the contrast metrics are defined using the magnitude of the noise, which is calculated based on the object and background RSS contrast. The contrast metrics are as follows:

$$M_8 = T_{\text{dTRSS}} = \sqrt{(\mu_t - \mu_b)^2 + \sigma_t^2}, \quad (23)$$

$$M_9 = T_{\frac{\text{dTRSS}}{\sigma_b}} = \frac{\sqrt{(\mu_t - \mu_b)^2 + \sigma_t^2}}{\sigma_b}, \quad (24)$$

$$M_{10} = T_{\frac{\text{dTRSS}}{\sigma_i}} = \frac{\sqrt{(\mu_t - \mu_b)^2 + \sigma_t^2}}{\sigma_i}. \quad (25)$$

Note that contrast metric $M_3 = M_8 / (\mu_t + \mu_b)$ and the contrast metric M_8 is used by the Army Night Vision and Electronic Sensor Directorate's software called NVThermIP (NVESD 2001). The contrast metrics M_8 through M_{10} take on values in the interval $[0, \infty)$.

In our case, any of the above contrast metrics can be used to assess the visibility of a given object. In the test plot, we can compute the ten contrast metrics for each of the four different objects, DP, DM, SP, and SM. The resulting contrast metrics are then combined into a single metric by using

PCA projections for all eight objects: the two deep objects, the two shallow objects, the two plastic objects, and the two metal objects.

For example, consider the thermal images in Figure 39, which shows three visibility scenarios: (a) all four objects are easily visible, (b) no objects are easily visible, and (c) only the shallow objects are easily visible. The corresponding computed contrast metrics for each object in each example image found are Tables 6, 7, and 8, respectively. When the objects are barely detectable by the human eye, the magnitude of the contrast metric is much smaller when compared to the contrast metrics computed for when the objects are easily detectable (see the highlighted rows in Table 8).

Figure 39. Thermal-image examples for (a) all four objects visible on 14 July 2018 at 0215 (b) objects not visible on 23 July 2018 at 0815, and (c) shallow objects visible on 2 September 2018 at 0930.

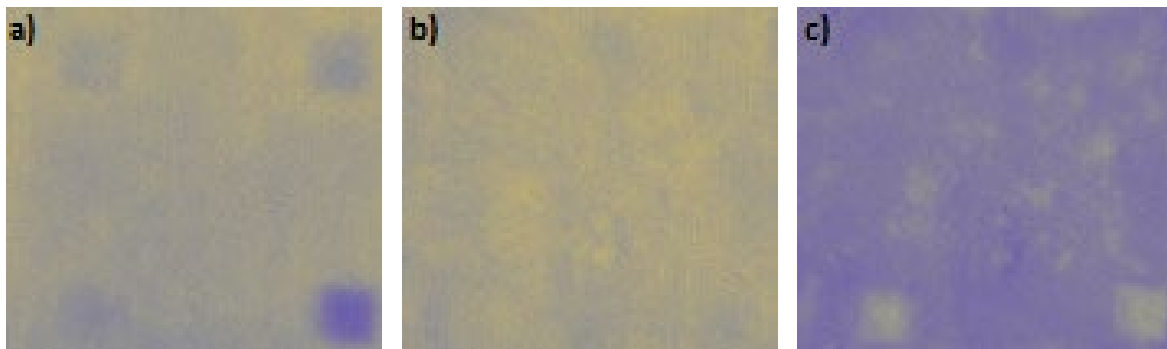


Table 6. Contrast metrics when all four objects are visible, shown in Fig. 39a.

Object	M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8	M_9	M_{10}
DM	-0.00178	-0.2609	0.00211	-1.1734	-1.509	-1.778	-1.0001	79.134	2.111	1.853
SM	-0.00215	-0.3527	0.00231	-1.825	-2.012	-2.467	-1.4627	85.669	2.630	2.144
DP	-0.00087	-0.1844	0.00106	-0.728	-0.849	-0.8501	-0.6599	39.805	1.042	1.041
SP	-0.00767	-0.5134	0.00805	-2.844	-2.934	-6.8183	-1.9345	298.835	7.158	3.080

Table 7. Contrast metrics when no objects are easily visible, shown in Fig. 39b.

Object	M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8	M_9	M_{10}
DM	0.00033	0.0536	0.00062	0.3505	0.4329	0.4253	0.3213	25.6154	0.8081	0.8224
SM	0.00017	0.0251	0.00065	0.1405	0.1697	0.1648	0.1298	26.444	0.6357	0.6547
DP	-4.44E-05	-0.007	0.00060	-0.0429	-0.0539	-0.0527	-0.0395	24.384	0.7148	0.7317
SP	-0.0006	-0.1292	0.00108	-0.4812	-0.6804	-0.6979	-0.4297	43.559	1.2611	1.2295

Table 8. Contrast metrics when shallow objects are easily visible, shown in Fig. 39c.

Object	M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8	M_9	M_{10}
DM	0.00089	0.04654	0.00223	0.2766	0.3613	0.3575	0.2523	90.197	0.8916	0.9010
SM	0.00782	0.39951	0.00913	1.4541	2.1352	3.0159	1.1857	370.686	3.5210	2.4928
DP	0.00497	0.02603	0.00159	0.1977	0.2519	0.2475	0.1814	64.418	0.7924	0.8067
SP	0.00879	0.32009	0.00992	1.6511	2.2382	3.2285	1.3177	403.869	3.6396	2.5232

This section introduced ten contrast metrics to assess the visibility of an object within an ROI in the thermal imagery. Each contrast metric is defined using a combination of either or both first- and second-order statistics calculated from the thermal image to bring out the object from the background noise. Next, further analysis of the contrast metrics is performed by assessing the distribution of the contrast metric for the Phase II data (Clausen 2021), which includes imagery for both before and after emplacement of the objects. As shown in the above tables, if each of the 10 contrast metrics for each of the 4 objects is considered, a collection of 40 contrast metrics for each image is obtained; however, a lower-dimension representation of these contrast metrics can be obtained by using the principal component projection of a collection of the contrast metrics to obtain a single contrast metric.

6.2.1 Analysis of contrast metrics

Analysis of the contrast metrics is further studied by looking at the distributions of the various contrast metrics. This will provide an understanding as to whether the contrast metrics make a good proxy for the thermal signature of the objects in the FLIR images. Recall we want to map the environmental variables to an object variable (function f in Figure 37), where the object variable serves as a proxy for the thermal images. The following analysis of the contrast metrics will help us decide whether the contrast metrics will be a satisfactory object variable for our purposes.

6.2.1.1 Distributions of the contrast metrics

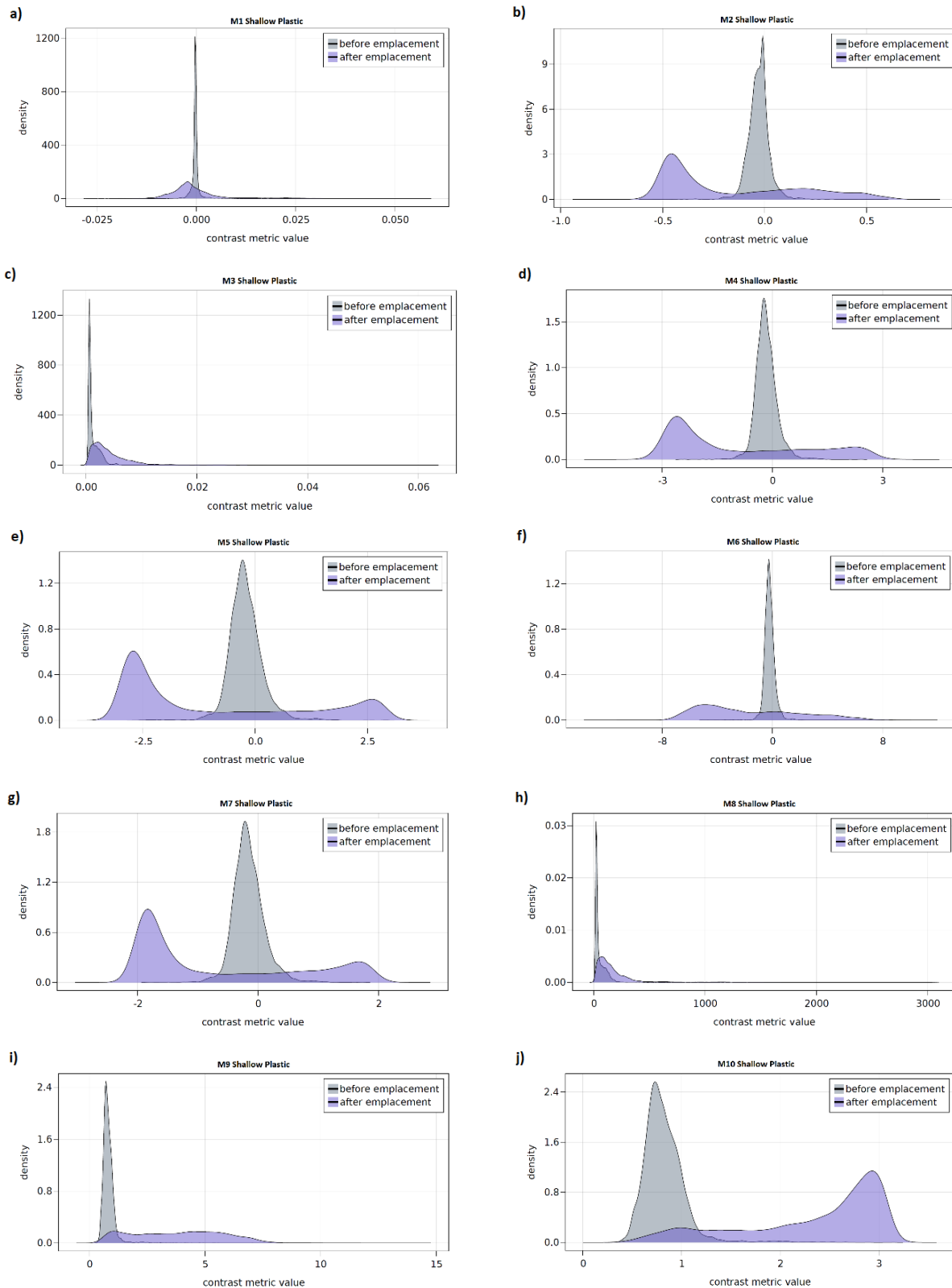
The contrast metrics introduced in the previous section allow us to identify how changes in the first- and second-order statistics of the thermal image can help detect a buried object in a scene. The Phase II test-plot dataset is used to analyze the contrast metrics as it contains data for both before and after emplacement of the buried objects. The distribution of the contrast-metric values for the entire Phase II dataset is separated into before and after emplacement periods to understand how buried objects in the scene change the distribution of the contrast metrics.

To illustrate this approach, the contrast metric M_1 through M_{10} for the SP object is used as an example. The qualitative qualities of the contrast-metric distributions for the other three objects can be extended from the SP object; however, the differences in the before- and after-emplacement distributions are the most pronounced for the SP object. Figure 40 shows the contrast-metric distributions for SP. There are a few common themes between the different contrast-metric distributions. First, there is a clear difference in the distributions of the contrast metrics before and after emplacement of the objects, which indicates these contrast metrics indeed help with identifying the objects from the background of the scene. Second, the distribution of the different contrast metrics when no objects are present is highly concentrated around zero for contrast metrics M_1 , M_2 , and M_4 – M_7 . This is expected since the numerator of these contrast metrics contains the signal $\mu_t - \mu_b$, which is approximately zero if there are no objects present. While for contrast metrics M_3 and M_8 – M_{10} , the before-emplacement distribution is concentrated about a positive number. This is because the numerator of these contrast metrics is given by the RSS

$$\sqrt{(\mu_t - \mu_b)^2 + \sigma_b^2},$$

which is approximately equal to σ_b prior to emplacement since $\mu_t \approx \mu_b$ is assumed.

Figure 40. For the SP object, a comparison of the before- and after-emplacement distribution of contrast metric (a) M_1 , (b) M_2 , (c) M_3 , (d) M_4 , (e) M_5 , (f) M_6 , (g) M_7 , (h) M_8 , (i) M_9 , and (j) M_{10} .



Lastly, the distributions for the contrast metrics after emplacement for the SP object is the most distinct from the before emplacement for all contrast metrics. This indicates that the SP object is easily identifiable through contrast-metric analysis of thermal images. For the SM object, the mean of the after-emplacement distribution is contained within the before-emplacement distribution, but there is still a distinct difference between the two distributions, indicating the SM object is not as easily identifiable when compared to the SP object. For each of the contrast metrics, the DP and DM objects have qualitatively similar distributions, while for the SP and SM objects the distributions are quite distinct. Note that the after-emplacement distributions for the SP and DP objects vary dramatically, while the distribution for the metal objects are more qualitatively similar in comparison.

6.2.1.2 PCA projection of contrast metrics and distributions

As noted above, some common themes are evident between the deep versus shallow objects, the metal versus plastic objects, and combinations of the two. It is desirable to have one single contrast metric capturing these features from the different contrast metrics to further study the effects of the different objects on the distributions of the contrast metrics. A lower-dimensional projection is obtained through a collection of contrast metrics by approximating it with the first component computed using PCA. The principal component projection is computed using the contrast metrics M_1 , M_2 , M_5 , and M_6 . In Tables 6–8, these four contrast metrics are highlighted in the yellow columns and are considered for a variety of reasons. First, each compares the signal $\mu_t - \mu_b$ to either the mean of the scene or the noise of the scene, which allows the contrast metrics to take on both positive and negative values. Second, these four contrast metrics require fewer algebraic operations to compute, and thus computing a large quantity of these metrics requires less computational storage. One could consider the collection of contrast metrics that include the RSS given by M_8 . However, these should be considered separately from the other contrast metrics as they take on only positive values and, due to the RSS involved, each computation requires more algebraic computation. Comparing M_5 with M_7 , the difference lies in the denominator, meaning M_5 is the signal simply divided by the noise of the scene while M_7 is the signal divided by the RSS of the image noise and object noise $\sqrt{\sigma_i^2 + \sigma_t^2}$. The noise of the object is considerably smaller than the noise of the image, so this noise RSS can be approximated by simply the noise of the image, thus M_5 is selected over M_7 in the PCA projection. Similarly, M_6 is used in the PCA projection

over M_4 , where the former is the signal divided by the background noise, σ_b , and the latter is the signal divided by

$$\sqrt{\sigma_b^2 + \sigma_t^2}.$$

Qualitatively, the distributions for the contrast metrics M_5 and M_7 are comparable and similar for M_6 compared to M_4 , which indicates no additional information is gained by including the contrast metrics M_4 and M_7 in the PCA projection.

The selected contrast metrics can be combined through PCA to obtain a single measurement or single contrast metric given by the first principal component. The projection of the four contrast metrics onto the first principal component allows us to obtain a combined contrast metric for each object (SP, SM, DP, and DM). We can also perform this projection for groupings of the objects to obtain a combined contrast metric for the shallow objects, the deep objects, the metal objects, the plastic objects, and all four objects. This means nine different contrast measures are obtained for each image, combining the information contained in the individual contrast metrics M_1 , M_2 , M_5 , and M_6 . For example, for the SP object,

$$M_{SP} = \text{PCA}(M_1, M_2, M_5, M_6)_{SP} = \sum_{i \in \{1,2,5,6\}} \frac{a_i (M_i^{SP} - \mu_i(M_i^{SP}))}{\sigma_i(M_i^{SP})}, \quad (26)$$

where M_i^{SP} is the i th contrast metric computed for the SP object, where $i \in \{1,2,5,6\}$, and $\mu_i(M_i^{SP})$ and $\sigma_i(M_i^{SP})$ are the mean and the standard deviation, respectively, of the i th metric, M_i^{SP} , computed for all images. For the Phase II dataset, the principal component projection coefficients (a_i) for the SP object are given by

$$\begin{bmatrix} a_1 \\ a_2 \\ a_5 \\ a_6 \end{bmatrix} = \begin{bmatrix} -0.463219 \\ -0.513571 \\ -0.510056 \\ -0.511388 \end{bmatrix}.$$

The above vector of projection coefficients corresponds to the first column of the projection coefficient matrix obtained from PCA. This can be done similarly for each object to produce M_{SM} , M_{DP} , and M_{DM} . For the groupings

of objects, consider the principal component projection for both SP and DP objects:

$$M_P = \text{PCA}(M_1, M_2, M_5, M_6)_P \sum_{j \in \{\text{DP}, \text{SP}\}} \sum_{i \in \{1, 2, 5, 6\}} \frac{a_{i,j} (M_i^j - \mu_i(M_i^j))}{\sigma_i(M_i^j)}, \quad (27)$$

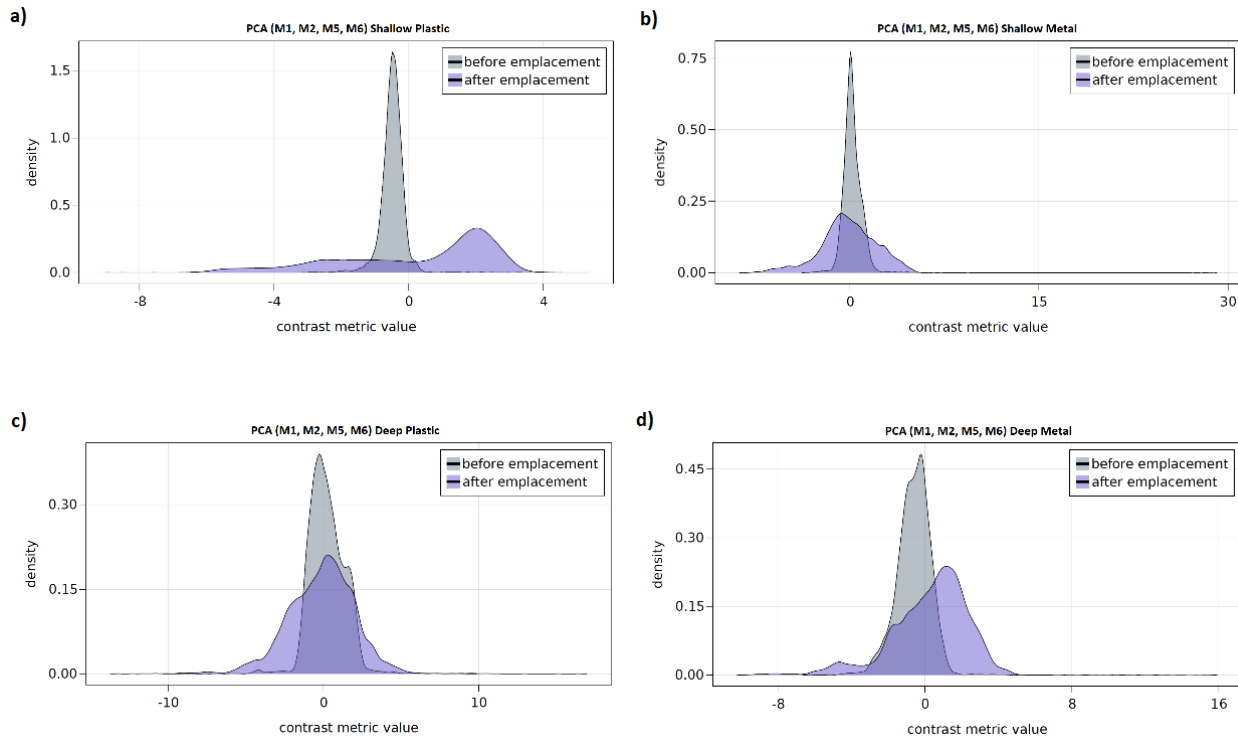
where M_P denotes the contrast-metric grouping for both plastic objects. Here, the projection coefficients, $(a_{i,j})$, are a matrix of values size 4×2 , the first column for the DP and second for the SP objects:

$$\begin{bmatrix} a_{1,\text{DP}} & a_{1,\text{SP}} \\ a_{2,\text{DP}} & a_{2,\text{SP}} \\ a_{5,\text{DP}} & a_{5,\text{SP}} \\ a_{6,\text{DP}} & a_{6,\text{SP}} \end{bmatrix} = \begin{bmatrix} -0.2763 & -0.3515 \\ -0.3437 & -0.3635 \\ -0.3705 & -0.3668 \\ -0.3746 & -0.3693 \end{bmatrix}.$$

Similarly, this projection can be done for the other groupings, which are both metal objects M_M , both shallow objects M_S , both deep objects M_D , and all four objects M_{ALL} .

As in the previous section, the before- and after-emplacement distributions of the PCA projection of M_1 , M_2 , M_5 , and M_6 are separated into the nine different metrics that can be computed for each image. Figure 41a–d shows the corresponding before- and after-emplacement distributions of the PCA projection contrast metrics M_{SP} , M_{SM} , M_{DP} , and M_{DM} . Note that the after-emplacement distributions are now centered about a positive number; but in Figure 40a, b, e, and f, the distributions are centered about a negative number. This change is because the projection coefficients are negative, which flips these trends. The larger separation between the before- and after-emplacement distributions indicates the ability of the contrast metrics to pull out the object from the scene noise. The SP object in Figure 41a is the most distinguishable, while the deep objects are relatively difficult to distinguish from the scene noise.

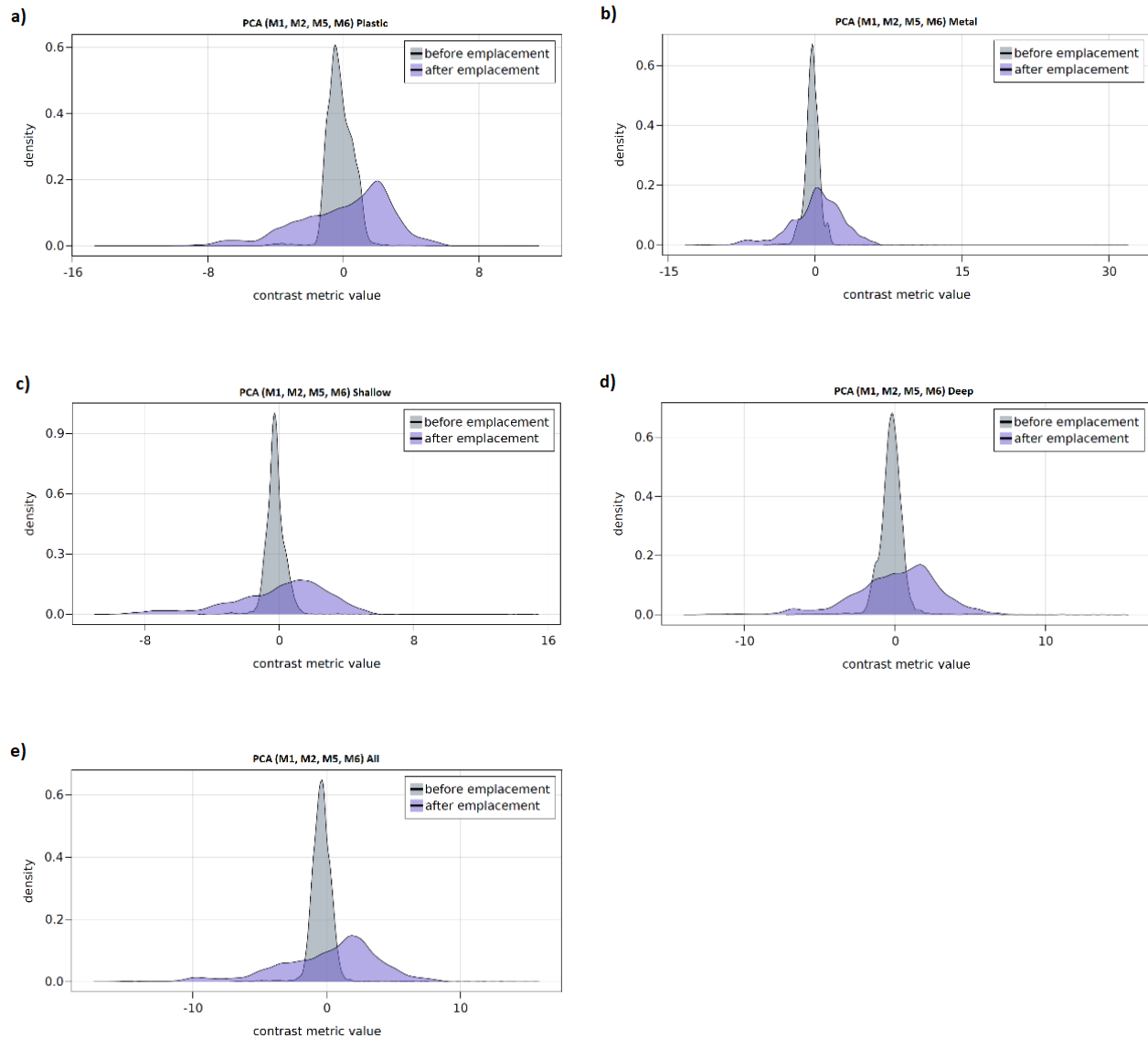
Figure 41. Comparing distributions of the PCA projection of the contrast metrics M_1 , M_2 , M_5 , and M_6 before and after emplacement for (a) the SP object, M_{SP} ; (b) the SM object, M_{SM} ; (c) the DP object, M_{DP} ; and (d) the DM object, M_{DM} .



Next, we analyze the difference between the before- and after-emplacement distribution of the PCA projection of the contrast metrics for the different groupings of objects. Figure 42 shows the distributions for (a) plastic, (b) metal, (c) shallow, (d) deep, and (e) all four objects. The PCA contrast metrics M_S , M_D , and M_{ALL} do not include the signatures for a mix of both the plastic and metal objects due to the groupings. In Figure 42c and d, the distribution comparisons for the shallow and deep groups are approximately the same, which indicates that, when object material is combined in a metric, the depth of the object does affect the ability of the contrast metric to pull out the object from the scene. When comparing the distributions for the plastic PCA contrast metric, M_P (Figure 42a), to the distributions for the metal PCA contrast metric, M_M (Figure 42b), there is a greater separation in distributions for the M_P , indicating plastic objects are easier to distinguish than the metal objects.

From the distributions for the plastic PCA contrast metric, M_P , it is evident that the plastic objects are easier to distinguish than the metal objects when compared to the distributions for the metal PCA contrast metric, M_M .

Figure 42. Comparing distributions of the PCA projection of the contrast metrics for groupings of the objects before and after emplacement for (a) plastic objects, M_P ; (b) metal objects, M_M ; (c) shallow objects, M_S ; (d) deep objects, M_D ; and (e) all objects, M_{ALL} .



In this section, we reviewed the effects of the emplacement of buried objects on the distribution of the chosen contrast metrics. We have seen that the presence of the buried objects changes the contrast-metric distribution when compared to before emplacement. Further, by combining multiple contrast metrics into a single metric by using a PCA projection, we can analyze these relationships further. In general, the SP object induces the largest change in the contrast-metric distributions, indicating this type of object can be detected from the scene noise using these contrast metrics. The metal objects (shallow and deep) are harder to differentiate from the

scene noise using contrast metrics, likely due to the conductivity of the metal, and the deep objects (plastic and metal) are the most difficult to detect from the scene noise. This analysis considered only bulk effects of buried objects in the scene on the computation of the contrast metrics, but one can expect that the time of day can influence the visibility of buried objects in thermal imaging. The next section analyzes the time-of-day relationship to the changing distributions of contrast metrics.

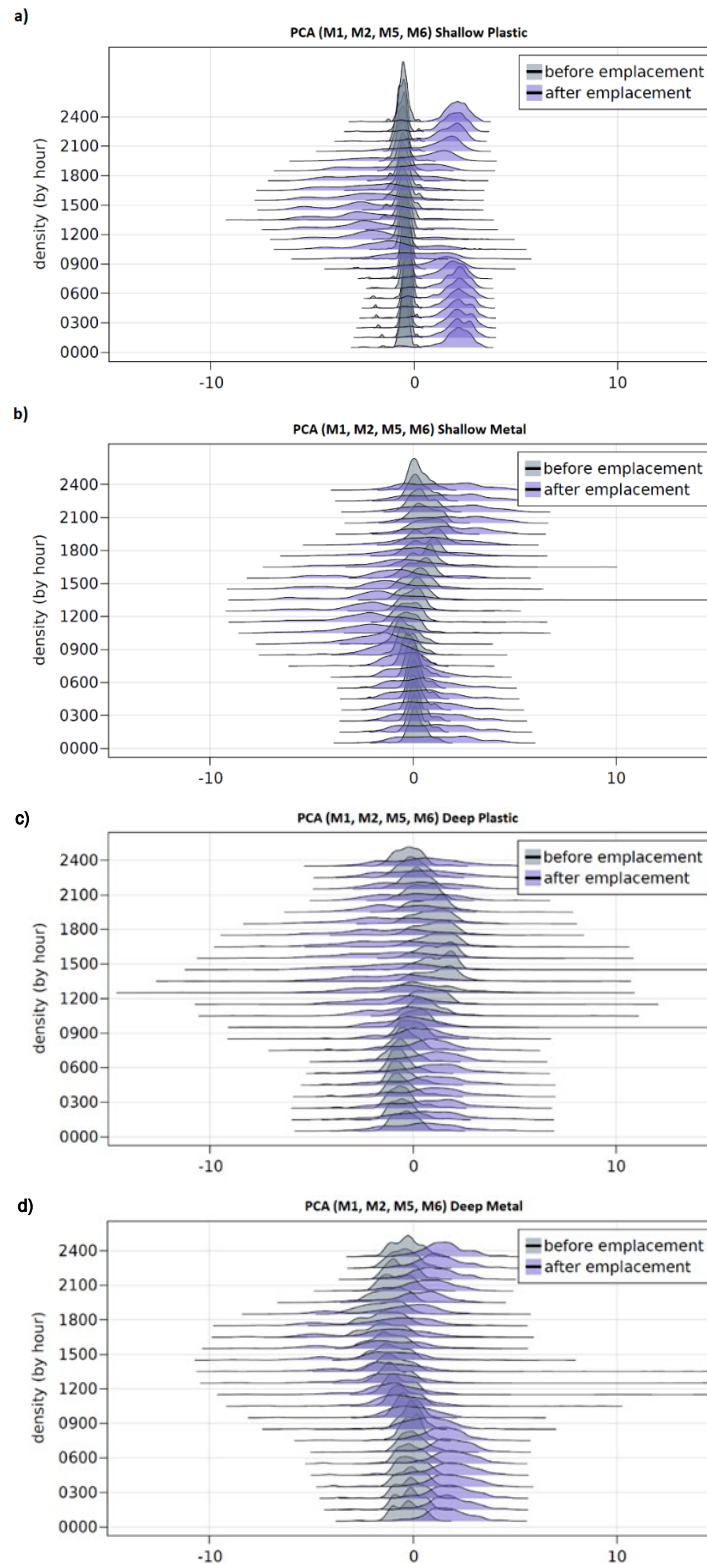
6.2.1.3 Effects of the time of day on contrast-metric distributions

Using the PCA contrast metrics described in the previous section, we evaluate the effect time of day has on these distributions. It is reasonable to assume that time of day will play a role in the ability to detect buried objects with thermal imaging because after the sun sets prior to thermal equilibrium setting into the soil and objects, the buried objects are likely to show a different thermal signature compared to the surrounding soil given their respective heat retention and conduction properties. Similarly, as the sun rises and begins to warm the soil, it is likely that there will be a time window in which the thermal signature of the buried objects differs from the surrounding soil as the thermal loading of the objects will occur at a different rate compared to the surrounding soil. Figure 43 investigates these relationships.

The ability to detect the buried objects using contrast metrics changes throughout the day, and the way in which it changes depends on the objects. First, we consider the SP object in Figure 43a. From 0000 to 0900 hours and 2100 to 2400 hours, the distribution for the SP object skews to the right of the before-emplacement distribution. Then in the middle of the day from 1000 to 1500, the distribution skews to the left; and in the transition times (i.e., 0900 to 1000 and 1600 to 2100), the distribution still differs from the before-emplacement distribution, but the width of the distribution indicates it is harder to distinguish the objects from the scene noise.

Second, we consider the SM object in Figure 43b. The distributions for after emplacement of the SM object vary by hour, but there are many fewer times in which the distribution is distinct from the before-emplacement distribution when compared to the SP object. Unlike the SP object, the SM object is more difficult to see in the middle of the night until midmorning (i.e., 0000 to 0700 and 2100 to 2400 hours). The SM object shows a distinct distribution in the middle of the day when the solar loading of the object is greater than the surrounding soil.

Figure 43. Assessing the effects of the time of day on the distributions of the PCA projection of the contrast metrics M_1 , M_2 , M_5 , and M_6 for (a) the SP object, M_{SP} ; (b) the SM object, M_{SM} ; (c) the DP object, M_{DP} ; and (d) the DM object, M_{DM} .



Thus, we see the distribution skew to the left of the before-emplacement distributions. Figure 43c shows the time-of-day distributions for the DP object, which show significantly less change by hour as compared to the SP object, indicating the deeper the object, the more difficult it is to pull out the thermal signature from the scene noise. Like the SP object, the DP object from 0100 to 0900 has a distinct distribution from before-emplacement distributions. However, in the middle of the day as the surrounding soil heats and the object temperature reaches equilibrium with the soil, the object is difficult to distinguish from the scene noise. This is indicated by the overlap of the before- and after-emplacement distributions for 1000 to 1400. Lastly, we consider the distributions by hour for the DM object shown in Figure 43d. Similar to the SM object, the DM object is difficult to detect in the middle of the day as the solar loading of the soil brings the object to thermal equilibrium with the surrounding soil, as seen with the overlap of the before-emplacement distributions with the after-emplacement distributions from 0900 to 1800. Outside these hours, the DM object can be detected from the scene noise as the before-emplacement distribution is skewed to the right when compared to the after-emplacement distributions.

In this section, we analyzed the performance of the chosen contrast metrics as object variables. We selected a subset of four contrast metrics, M_1 , M_2 , M_5 , and M_6 to represent the visibility of the four buried objects within the test plot. Further, we aggregated these selected contrast metrics into a single measure by projecting the metrics onto the principal component computed with PCA. For each thermal image, we can compute nine of these aggregated contrast metrics to study the individual objects (SP, SM, DP, and DM), the plastic objects, the metal objects, the shallow objects, the deep objects, and all four objects together. Next, we will use ML to model the nonlinear relationship between the environmental conditions and these contrast-metric object variables.

6.3 Machine learning approach to mapping environmental variables to object variables

Our goal is to understand the relationship between the environmental variables and the object variables as this provides a connection between environmental phenomenology and the thermal images. For the object variable, we use the contrast metrics defined in the previous section and specifically the PCA projection of the contrast metrics for M_1 , M_2 , M_5 , and M_6 . Studying the nine PCA projection contrast metrics— M_{SP} , M_{SM} , M_{DP} ,

M_{DM} , M_S , M_D , M_P , M_M , and M_{ALL} —we can determine which environmental factors influence the visibility of each object and each object grouping. Our aim is to obtain a mapping between the environmental variables and the object variables and also an interpretable functional relationship between the variables. Ideally, we can use a linear model to map the environmental variables to the contrast metrics because we can easily interpret a linear model. However, a nonlinear model is better suited for the task of modeling this complex relationship, but the higher fidelity in the modeling comes at a cost of interpretability. When referring to interpretability, we want to be able to understand which environmental variables have the strongest influence on the contrast-metric prediction. This is what we investigate in the next sections.

6.3.1 Nonlinear mapping between environmental variables and the object variables

To model the complex relationship between the environmental variables and the PCA contrast metrics, we employ ML. However, the cost of using ML to model the nonlinear relationship between the variables is the ability to explain which environmental variables play the biggest role in this relationship. We use a boosted trees algorithm called EvoTrees (EvoTrees 2019), and we pair this model with Shapley analysis (Lundberg and Lee 2017) to interpret the results. Shapley analysis produces for each environmental variable a SHAP number, which represents the response of the object variable prediction to the environmental feature. SHAP values are between 0 and 1; and the closer the value is to 1, the more important the feature response is for the object variable prediction. The sum of the SHAP values for environmental features is 1. We also use the ML algorithm TabNet (Arik and Pfister 2020), which is a tabular learning method that has a built-in explainability metric that is like the SHAP values. In TabNet, the explainability can be done globally (i.e., measure the importance of each environmental input in the prediction of the output, which is analogous to the Shapley analysis process). The global explainability measure in TabNet is not an approximation procedure while Shapley analysis provides an approximate measure. However, TabNet also offers interpretability within the learning to understand how the algorithm is using the environmental variables at each step of the network to yield the result of predicting the environmental variables. The idea here is to learn the functional relationship between the input and output variables rather than learning a series of weights as is done in a neural network. For instance, we let $x \in X$ be a vector containing the environmental variables for a particular timestamp

and let y be one of the corresponding PCA contrast metrics. Then, we are seeking to learn a function $f: \mathbb{R}^m \rightarrow \mathbb{R}^n$ such that $f(x) \approx y$. We cannot learn this relationship exactly, so the learned function f will give us predicted values for the contrast metrics. Particularly, we set

$$\hat{y} = f(x), \quad (28)$$

where $\hat{y}$ is the approximations to the actual contrast-metric values y . Then, in the learning process, we minimize a loss function $L(y, f(x))$ to find the best fitting function f so that the approximation $\hat{y}$ is close to the actual values y . The form of the loss function varies between methods, and the specific loss function used with boosted trees and TabNet will be explicitly stated in the next sections.

In general, we train the ML algorithms by randomly splitting the data into training, validation, and testing datasets. The test dataset is not used in the training process and is our measure for how well the training learned the desired function. The validation informs the training process and helps determine how well the training is progressing and can be used to correct the learning process. We have the entire environmental dataset for input,

$$X = (x_i)_{i=1}^M \text{ for } x_i \in \mathbb{R}^n, \quad (29)$$

and the entire contrast-metric dataset for the output or label,

$$Y = (y_i)_{i=1}^M \text{ for } y_i \in \mathbb{R}^m. \quad (30)$$

For the iid environmental data, each vector of environmental data, x_i , is contained in $\mathbb{R}^{10}$; and if we select one single contrast metric at a time for the output, then each vector of output environmental data is a single real number. When considering after-emplacement data for 2018, the total number of observations is $M = 34,657$; and if considering both before and after emplacement data in 2018, the total number of observations is $M = 47,990$. To create the training, validation, and testing sets, we randomly selected a subset of both X and Y as follows:

$$\left(X_{\text{train}} = (x_j)_{j=1}^{M_{\text{train}}}, Y_{\text{train}} = (y_j)_{j=1}^{M_{\text{train}}} \right) \text{ where } \frac{M_{\text{train}}}{M} = 0.8. \quad (31)$$

In a similar fashion, we selected X_{valid} , Y_{valid} , X_{test} , and Y_{test} such that $\frac{M_{\text{valid}}}{M} = 0.1$ and $\frac{M_{\text{test}}}{M} = 0.1$.

To measure the accuracy of the predictions produced by the ML model, we use four different error metrics. First is the mean absolute error (MAE), which is defined as

$$E_{\text{MAE}}(X, Y) = \frac{\sum_{k=1}^P |y_k - f(x_k)|}{P}, \quad (32)$$

where $f(x_k) = \hat{y}_k$ is the ML prediction of the output given the k th input variable and y_k is the *true* value of the output variable. The number P represents the total number of observations in the given input and output sets, which can be the training sets, validation sets, or the testing sets. Second, we have the mean square error (MSE), which is defined by

$$E_{\text{MSE}}(X, Y) = \frac{\sum_{k=1}^P (y_k - f(x_k))^2}{P}. \quad (33)$$

The next error metric is defined in terms of the MSE and is called the root mean square error (RMSE):

$$E_{\text{RMSE}}(X, Y) = \sqrt{E_{\text{MSE}}(X, Y)}. \quad (34)$$

Lastly, we have the normalized mean square error (NMSE),

$$E_{\text{NMSE}}(X, Y) = \frac{\text{var}(Y - f(X))}{\text{var}(Y)}. \quad (35)$$

The notation $Y - f(X)$ indicates that we are interpreting $Y \in \mathbb{R}^P$, where P is the total number of observations considered in that set and $f(X) \in \mathbb{R}^P$ is the vector of predictions for all inputs in the set X . Then var is interpreted as computing the variance of the respective vector, either the difference between the true and predicted outputs or the entire true output set. The normalized error metric considers the overall variance of the output set and thus results in a much smaller error than the other three considered errors. The value of E_{NMSE} is always less than one while the other considered errors can have values much greater than one.

Next, we apply two different ML algorithms to learn the relationship between the environmental variables and the PCA contrast metrics.

6.3.1.1 Boosted trees method

First, we will consider modeling the relationship between the environmental variables and the PCA contrast metrics using a boosted trees method, specifically using the EvoTrees implementation in the Julia software language. The idea of gradient-boosted trees is to recursively learn the function $f(x)$ that represents the mapping between the input variables, x , and the output variables, y . Note, that we have a set of M input variables $(x_i)_{i=1}^M$ where each $x_i \in \mathbb{R}^m$ and a set of M output variables $(y_i)_{i=1}^M$ where each $y_i \in \mathbb{R}^n$.

In our case, the input variables are the environmental conditions, and the output variables are contrast metrics. Gradient boosting combines “weak” learners (i.e., trees) to create a “strong” learner. For example, consider starting with an initial representation of f applied to each pair of $(x_i, y_i)_{i=1}^M$:

$$F(x_i) = \hat{y}_i, \quad (36)$$

where $\hat{y}_i$ approximates the *true* object variable y_i . Now, to correct this approximation, we add a function h that attempts to make this approximation better to obtain a *new* approximation for each $i = 1, \dots, M$:

$$F(x_i) + h(x_i) = \hat{y}_i, \quad (37)$$

where the correction model h ,

$$h(x_i) = \hat{y}_i - F(x_i), \quad (38)$$

is equal to the residual between the approximation and the function we want to model, F . If we choose to minimize the loss function to be the MSE,

$$L(x, y) = \frac{1}{2} (y - F(x))^2, \quad (39)$$

then the residual h is equal to the negative gradient of the loss function L , and we learn the regression tree, h , by minimizing the loss given the set of

residuals. This is where the idea of gradient boosting comes into play. We are “boosting” the model through the information contained in the gradient. This process can be repeated to further refine the model by adding another regression tree to be fit to the new set of residuals. This is the core idea of gradient-boosted trees—it is an additive tree model fitted using gradient descent methods.

Aside from this example, other loss functions may be used; then the correction model h is not necessarily equal to the residual, but it will be the negative gradient of the loss. Further, by correcting the model with the negative gradient of the loss, this progresses the learning such that we find the minimum of the loss function for which the minimizer approximates the actual output variables y . To see this, we define a loss functional J , which is the sum of the loss function over all data points

$$J = \sum_i L(x_i, y_i). \quad (40)$$

Then the necessary condition for finding the minimum of J requires the gradient of J to be zero:

$$\frac{\partial J}{\partial F(x_i)} = -(y_i - F(x_i)) \approx 0 \quad (41)$$

for each i , thus we have $y_i \approx F(x_i)$ for $i = 1, \dots, M$. The idea of gradient boosting was introduced in (Friedman 2001) and has since been used to develop several algorithms based on gradient boosting, including EvoTrees.

In the application of gradient-boosted trees to our problem, we use a linear loss function, which is given by

$$L(x, y) = |y - f(x)|. \quad (42)$$

This loss function is selected because the absolute difference between the prediction $f(x)$ and actual output y reduces the importance of outliers in the learning process. If we were to use the square error, then the error for outlier points in the data is squared and has a high impact on the learning, as we are trying to minimize the loss function; thus, the learning is prone to overfitting the outliers.

Next, we apply the EvoTrees implementation of the gradient-boosted trees method to predict the contrast metric from the environmental conditions for a given thermal image of the test plot.

The chosen gradient-boosted trees implementation, EvoTrees, is written in the language Julia; and the ML package, MLJ, offers a framework in which fine-tuning the model's hyperparameters can be done with ease (Blaom et al. 2020). We apply the gradient-boosted trees method to two categories of contrast metrics: the PCA contrast metric for all objects and the PCA contrast metric for SP objects.

After optimizing the hyperparameters for the boosted trees model, it is trained using the training and validation subsets of the environmental variables and the selected contrast metrics. The overall performance of the model is measured using the test dataset. In this case, we are going to train the boosted trees model on both the PCA all contrast metric and the PCA SP contrast metric and will compare the results. Note that when the output variable changes, the process to tune the hyperparameters must be repeated as the tuning also depends on the chosen output variable. First, we apply this method to the PCA contrast metric for all four objects. Figure 44 compares the training and testing errors for the gradient-boosted trees model trained on the after-emplacement data with the output variables as the PCA contrast metric for all four variables. The error is measured in the four error metrics described above, MAE, MSE, NMSE, and RMSE. The blue bar represents the error computed on the test data, and the orange bar represents the error computed on the training data. Since the test error across all four error metrics is larger than the training error, this indicates overfitting occurred in this process. This means the learned gradient-boosted trees model was overfit to the training data and it is not as generalizable to data unseen by the learned model. Regardless of the overfitting observed here, the boosted trees model seems to have learned the relationship between the environmental variables and the PCA contrast metric for all four objects relatively well, indicated by the small value of the error metrics in both the testing and training data.

The EvoTrees implementation of gradient-boosted trees contains a metric called normalized gain, which is a measure of the feature importance in the resulting model. This provides a measure of how much each environmental variable played a role in the resulting learned model. In Figure 45, the four most important environmental variables in the formation of the

learned model are the incoming solar radiation, the soil water content, the average air temperature, and the average relative humidity. The least important environmental variables are the average snow depth, the average wind speed, and the rain total. Interestingly, the rain total variable is not nearly as important as the soil water content given the two variables are clearly related. However, the rain total is measured every 5 minutes and is not a cumulative total over a long period of time, while the soil moisture content is affected by rain events long after the rain hits the ground, which is one reason why the soil moisture content is much more important than the rain amount in terms of the relationship between the environmental variables and the contrast metric for all four objects.

Figure 44. A comparison of the training and testing errors for the gradient-boosted trees model trained with the PCA contrast metric for all four objects.

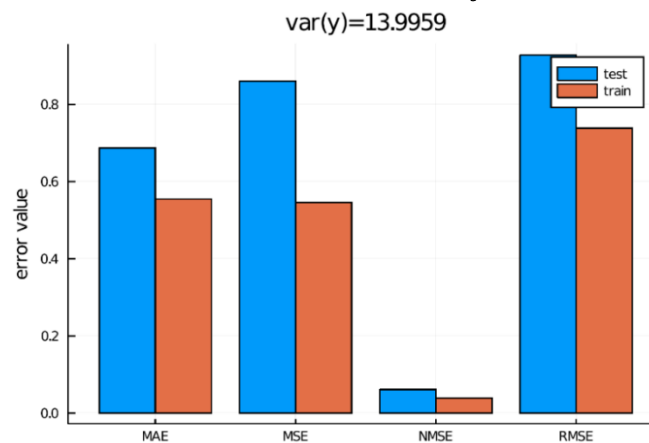
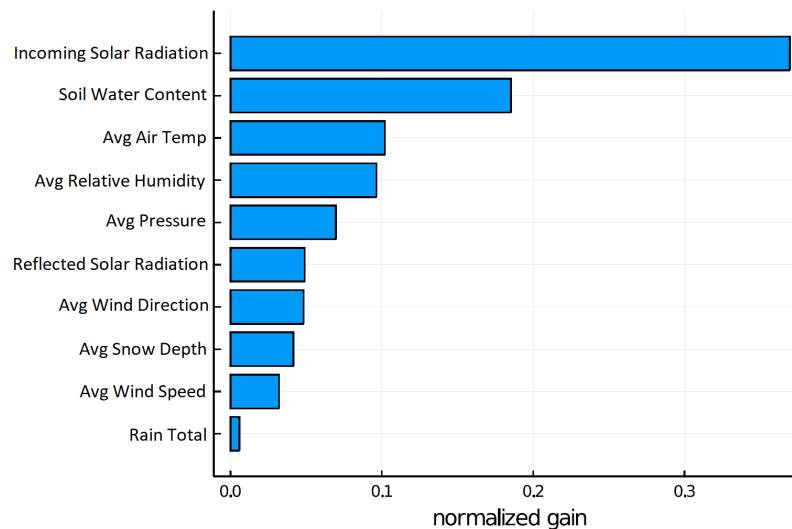
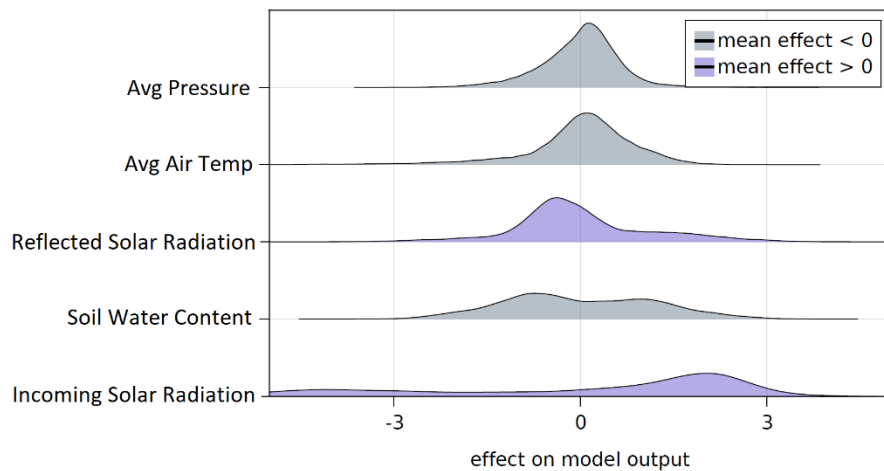


Figure 45. The normalized gain values for the gradient-boosted trees model with the output variables given by the PCA contrast metric for all four objects.



Shapley analysis can be used to understand whether each of these environmental variables positively or negatively affects the prediction of the corresponding contrast metric. Figure 46 shows the Shapley value density for the average pressure, average air temperature, average reflected solar radiation, soil water content, and average incoming solar radiation. The pressure, air temperature, and soil water content all have a mean negative effect on the learned model, and the incoming and reflected solar radiation both have a mean positive effect on the learned model. The environmental variables with a mean positive effect generally aid in the prediction of the contrast metric, while the environmental variables with a mean negative effect make it more difficult to accurately predict the contrast metric.

Figure 46. The normalized gain values for the gradient-boosted trees model with the output variables given by the PCA contrast metric for all four objects.

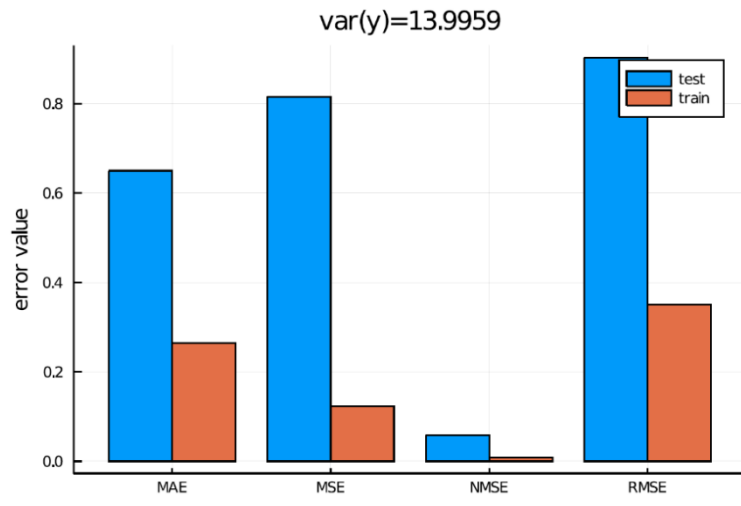


In this section, we consider training a gradient-boosted trees model with input variables given by sequential environmental variables to determine whether the inclusion of the sequential nature of the environmental conditions aids in the performance of the learned model. Recall that the sequential environmental variables are computed using the software package `tsfresh` and are computed to incorporate the 6 hours of data before the current timestamp. The sequential relationships are approximated through a variety of methods from linear approximations to time-reversal statistics to fast Fourier transform approximations. We apply the gradient-boosted trees method with the sequential environmental variables as the input and the PCA contrast metric for all four objects as the output. Due to the additional sequential variables computed with `tsfresh`, each sequential environmental input

$$x_j^{\text{seq}} \in \mathbb{R}^{7900},$$

where there are 790 sequential approximations for each of the ten iid environmental variables. The gradient-boosted trees model was optimized using learning curves and then trained on this dataset, and Figure 47 shows the resulting errors. In this case, the corresponding training error metrics have decreased by about half compared to only using the iid environmental variables as the input. However, this model suffers even more from overfitting as the testing error shows hardly any improvement when compared to the iid environmental input model. By pairing the sequential approximations to the environmental variables, we greatly increase the complexity of the input variables, yet we do not reap any benefits in terms of a widely applicable model to unseen data. If the model showed a corresponding decrease in the testing error metrics, then this is a viable route to improve the learned model. The trade-off for increased complexity does not pay off in this case, and it is best to consider the simplified model with only iid environmental variables.

Figure 47. A comparison of the training and testing errors for the gradient-boosted trees model trained with sequential environmental data and the PCA contrast metric for all four objects.



6.3.1.2 TabNet method

In this section, we consider a second ML algorithm called TabNet, which was first introduced by Arik and Pfister (2020). TabNet is a deep neural-network learning framework with an architecture specifically designed for learning on tabular data. In particular, TabNet has a built-in normalization procedure so tabular data can be input without implementing

preprocessing procedures. Furthermore, TabNet uses sequential attention transformers and feature transformers to select the most relevant features at each decision step. The sequential attention affords one the ability to interpret the results of the learned model without any supplemental interpretability algorithms like Shapley analysis (Lundberg and Lee 2017) or Local Interpretable Model-Agnostic Explanations (LIME; Riberio et al. 2016). The sequential attention is used to compute learnable masks in each step of the network for soft selection of salient features in the learning process. If the value of the mask for a particular feature is closer to zero, then that feature is less important in the overall learning process. These masks are the key to the interpretability feature of TabNet; they provide both local importance at each step of the algorithm, and the masks can be aggregated to formulate a global importance value for each of the features. The number of masks used in the algorithm is tied into the number of decision steps employed, which is a hyperparameter to be tuned. The larger the number of steps, the more likely the algorithm is to suffer from overfitting. We found that for our application to predict the contrast-metric value from the environmental data, three steps are sufficient, so we used three of these learnable masks throughout the learning process.

Let $M^i \in \mathbb{R}^{B \times D}$ be the mask in the i^{th} step of the algorithm where B is the batch size and D is the number of features. The batch size indicates the number of samples used in the batch normalization step, which is a feature of TabNet that allows one to process tabular data without any preprocessing or global normalization of the data. The batch size is yet another hyperparameter to be tuned, and it is a percentage of the total training data to be considered in each batch. If $M_{b,j}^i = 0$, then the j^{th} feature of the b^{th} sample bears no importance on the decision process in the i^{th} step of the algorithm. The values of the mask at the given step provide insight into the local importance of each feature in the decision process. The masks can then be aggregated to formulate a global importance for each feature for the learned model. The aggregation process uses a coefficient that combines the masks at different steps, which can weigh the relative importance of each step in the decision process. The result yields a vector $M^{\text{agg}} \in \mathbb{R}^D$ where each entry of the vector indicates the relative importance of each feature for the entire learned model where $M_j^{\text{agg}} \in (0,1)$ and $\sum_j M_j^{\text{agg}} = 1$.

Next, we apply the TabNet algorithm to the iid environmental data and the PCA contrast metrics. To train the TabNet models, we use the MSE

loss function. The implementation of TabNet in Python used here is found at Dreamquark-AI (2020). As before with the boosted trees model, we optimize the hyperparameters of TabNet through fine-tuning prior to training the model. We will assess the feature importance for each of the nine different contrast metrics to gain a better understanding of which environmental variables are more important to the different objects or object groupings.

First, we consider the PCA contrast metric for all four objects for a comparison with the previous EvoTrees implementation. Figure 48a shows the four error metrics computed for the training and testing datasets with the iid environmental variables, and Figure 48b shows the corresponding feature importance computed with TabNet's sequential attention feature. Note that we selected a different random selection of the full set of environmental variables and contrast metrics for the training, testing, and validation sets when compared to the EvoTrees implementation. Comparing to the errors in Figure 44, we still see some evidence of overfitting in the TabNet errors; however, the values of the test errors and the training errors are much closer when compared to the errors for the EvoTrees implementation. This indicates that the learned TabNet model can better predict the corresponding contrast metric for data not seen during the training process. Also note that the training errors are approximately the same with TabNet when compared to the EvoTrees method, but the testing errors are smaller when compared to the EvoTrees method. This indicates that TabNet is better suited to learning the relationship between the environmental variables and the chosen contrast metric. In Figure 48b, the corresponding global feature importance is shown for the learned TabNet model. The four most important environmental variables are the average incoming solar radiation, the average relative humidity, the soil water content, and the average air temperature. When compared to the EvoTrees model in Figure 48, we see that the top four most important environmental factors are the same four variables; however, the ordering of the variables does differ. Note that in both cases, the incoming solar radiation is the most important environmental factor, which makes sense since we are using thermal imaging to detect the buried objects and the thermal loading of the soil and objects is directly related to the amount of incoming solar radiation.

Using the learned TabNet model for the PCA contrast metric for all four objects, we compare the predicted contrast-metric value to the actual contrast-metric value in the test dataset. In Figure 49, for the test set, we plot

the true contrast metric against the predicted contrast-metric value. Here, the orange line indicates a perfect prediction; and the farther the scatter plot deviates from this line, the more the predicted contrast metric differs from the true value. Next, we apply the TabNet algorithm to the contrast metrics computed for each individual object.

Figure 48. A comparison of the training and testing errors for the TabNet model with the PCA contrast metric for all four objects as (a) the output and (b) the corresponding feature importance for the learned model.

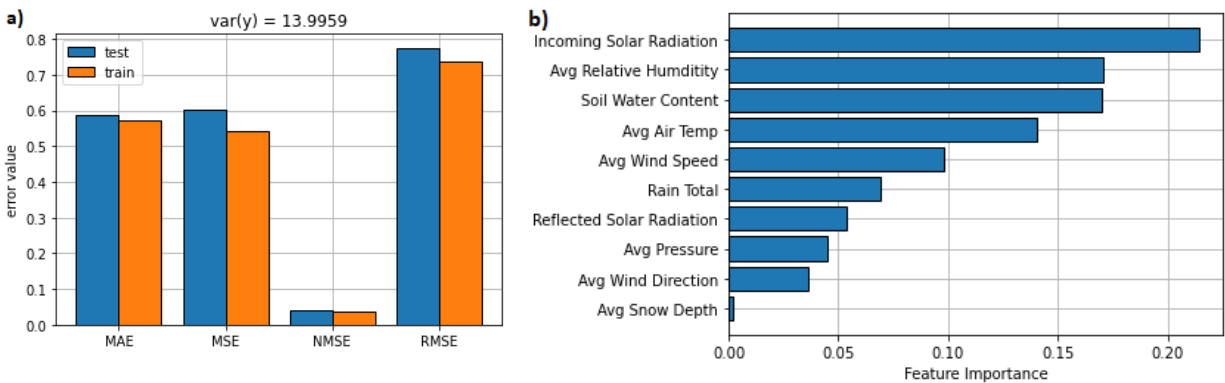


Figure 49. A comparison of the true contrast metric for all objects with the predicted value using the TabNet model. The orange line represents a perfect prediction.

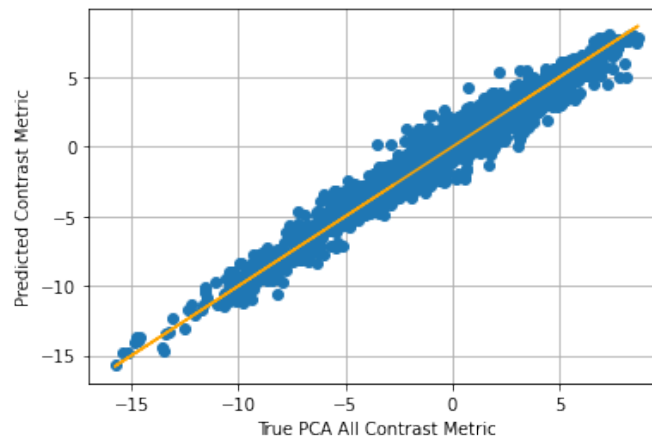
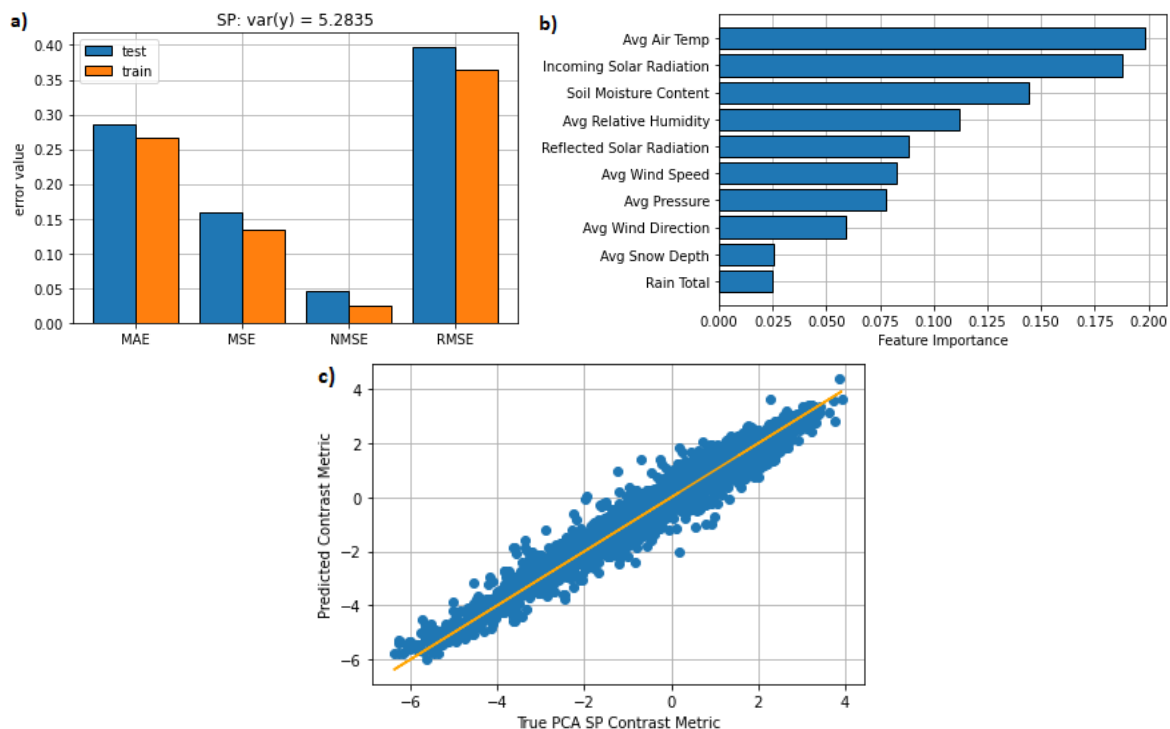


Figure 50a compares the testing and training errors for the TabNet model trained with the contrast metric for the SP object; and we can see that, overall, both the training and testing errors are smaller for the SP object compared to all four objects in Figure 48a. This indicates that the SP object is more easily modeled with the environmental variables. Figure 50b shows the feature importance for the SP model, and we see that the four most important environmental features are the average air temperature,

average incoming solar radiation, the soil moisture content, and the average relative humidity, which are the same four variables that make up the most important environmental variables for the model for the contrast metric with all four objects. Lastly, Figure 50c compares the true SP contrast metric versus the predicted SP contrast metric using the TabNet model. As before, the orange line represents a perfect prediction.

Figure 50. A comparison of the test and training errors for TabNet with (a) the SP object, (b) the corresponding feature importance for the SP model, and (c) a comparison of the predicted SP contrast metric with the true value.



In Figure 51, we have the same plots for the SM object, and there are a few things to note here. For the SM object, the training and testing errors are slightly larger compared to the SP objects but are still overall lower than the errors for all four objects. The four most important environmental variables are nearly the same except the average relative humidity is replaced by the average reflected solar radiation. Figures 52 and 53 show the same corresponding plots for the two deep objects, DP and DM, respectively.

Figure 51. A comparison of the test and training errors for TabNet with (a) the SM object, (b) the corresponding feature importance for the SM model, and (c) a comparison of the predicted SM contrast metric with the true value.

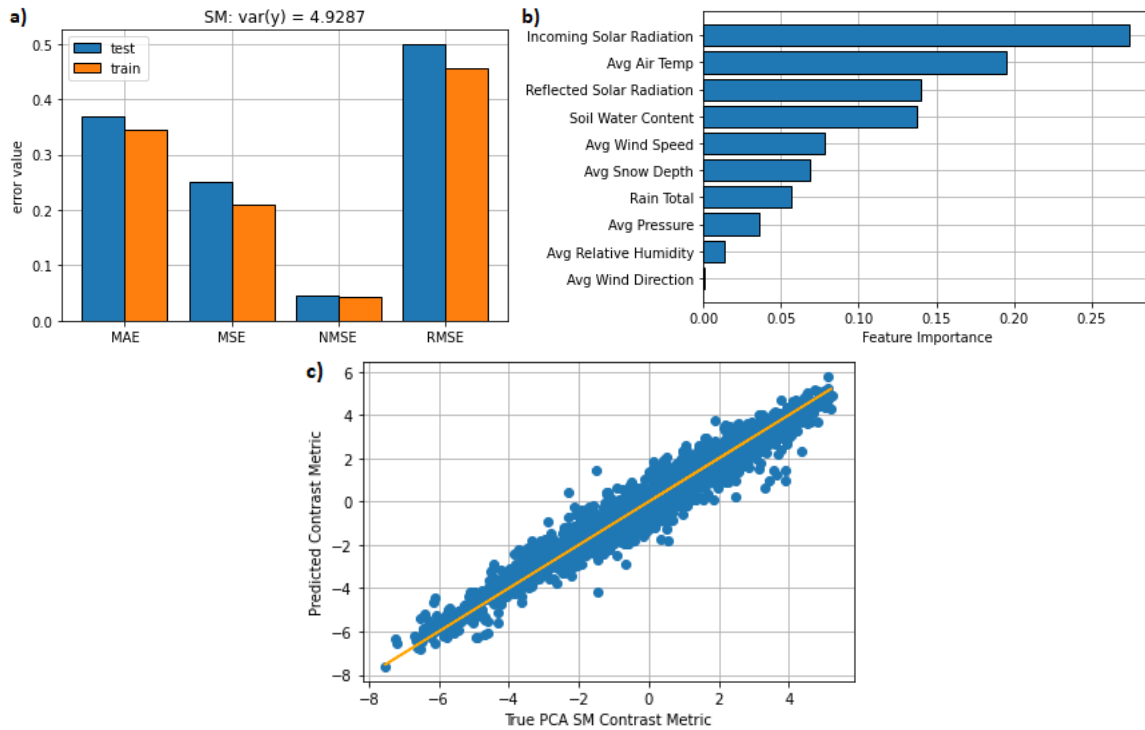


Figure 52. A comparison of the test and training errors for TabNet with (a) the DP object, (b) the corresponding feature importance for the DP model, and (c) a comparison of the predicted DP contrast metric with the true value.

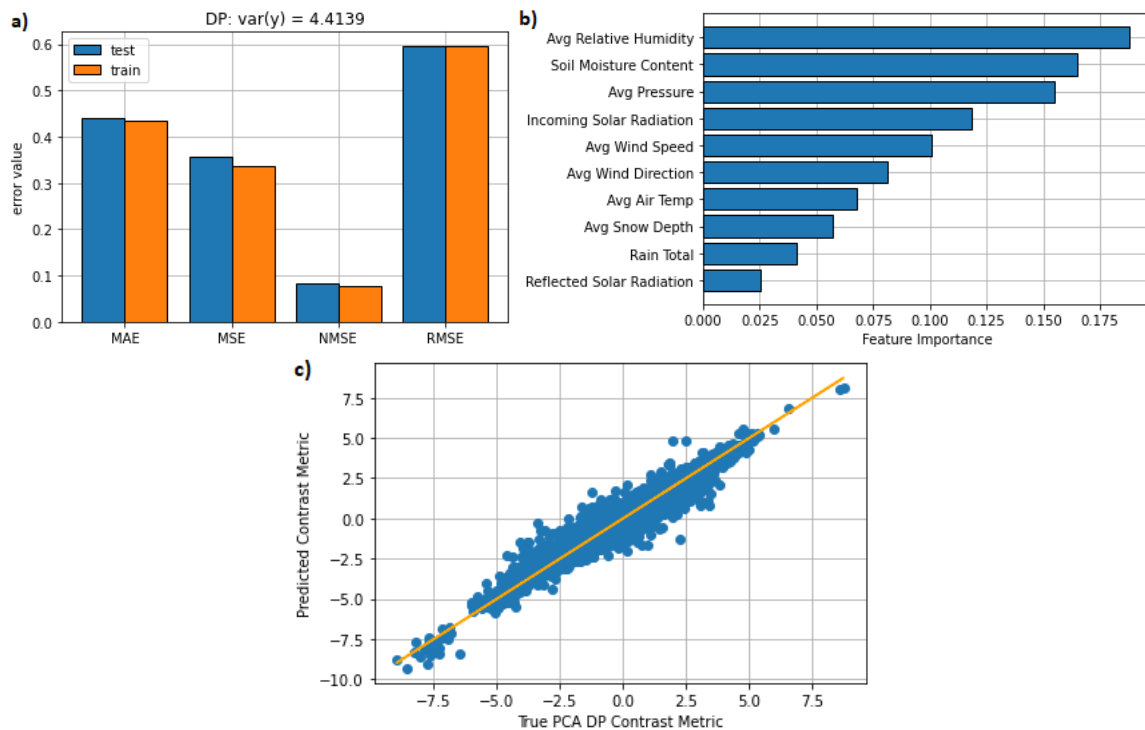
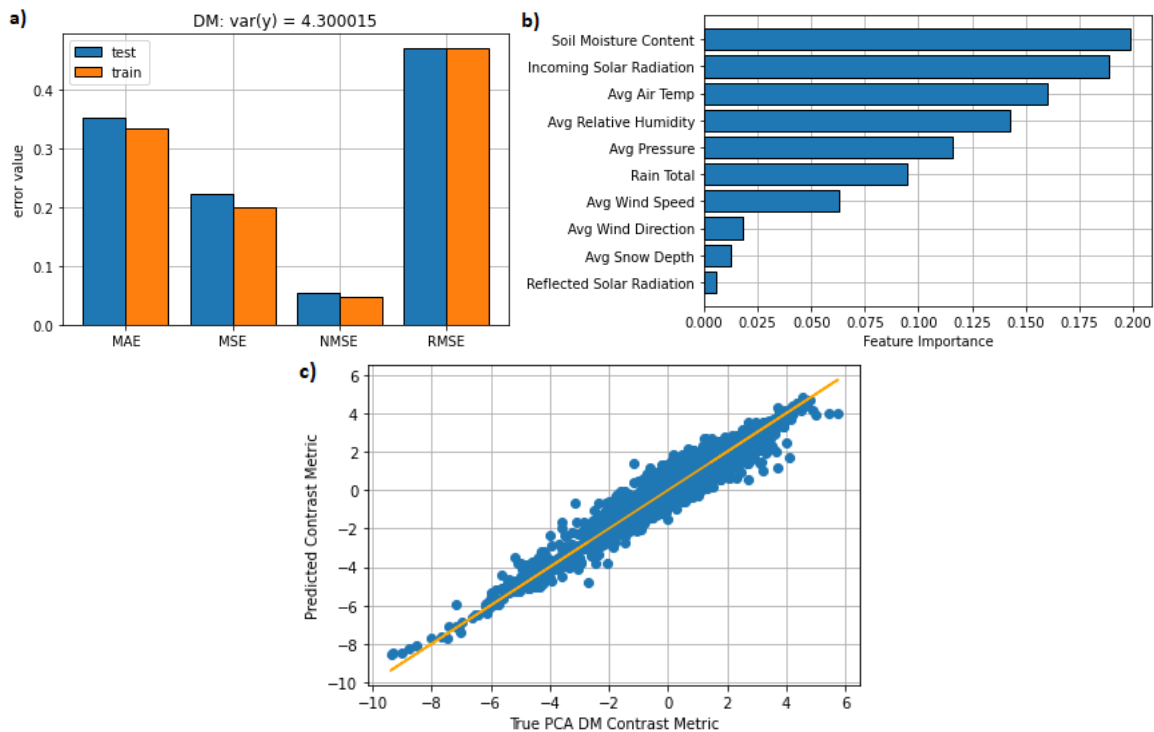


Figure 53. A comparison of the test and training errors for TabNet with (a) the DM object, (b) the corresponding feature importance for the DM model, and (c) a comparison of the predicted DM contrast metric with the true value.

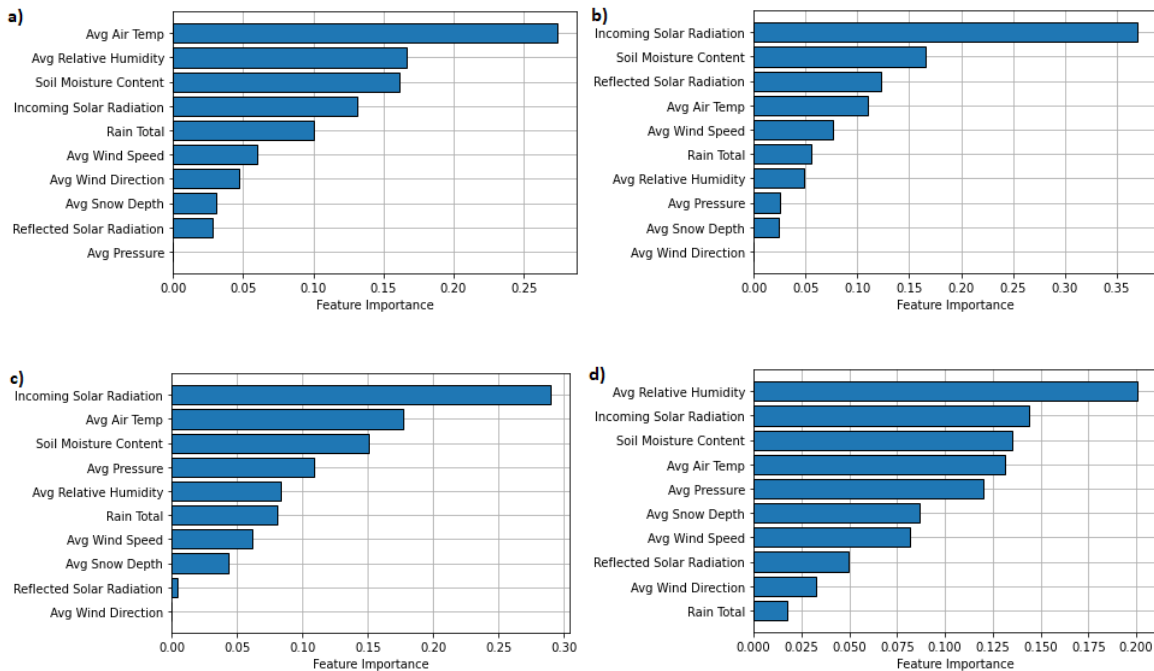


For the DP object in Figure 52, the errors indicate minimal overfitting occurred with the test data set and training data set as the test errors between the two datasets are nearly identical, and the four most important environmental variables consist of the same set as we saw for SP and all four objects. In Figure 50c, we see two separate clusters of points, one on the bottom left of the plot and one large cluster in the middle between -5 and 5. Lastly, in Figure 53, for the DM object, we yet again see that the four most important environmental factors remain the same and that the training versus testing errors show minimal overfitting as we saw for the DP object. In Figure 53c, the predicted values of the contrast metric for DM tend to deviate more when compared to the other three objects, but the predictions are still clustered about the orange line that indicates a perfect prediction.

Finally, in Figure 54a–d, we see the feature importance for the object groupings for the plastic objects, metal objects, shallow objects, and deep objects, respectively. For the plastic, metal, and deep objects, the four most important environmental factors remain the same: incoming solar radiation, soil moisture content, average air temperature, and average

relative humidity. However, in Figure 54c for the shallow objects, the average relative humidity is replaced by average air pressure.

Figure 54. The feature importance for (a) plastic objects, (b) metal objects, (c) shallow objects, and (d) deep objects.



In this section, we have identified the most important environmental variables in terms of predicting the contrast metrics from the environmental variables. In the next section, we will use this information to create an environmentally informed ATR algorithm that takes as an input the most important environmental variables identified here.

6.4 Environmentally Aware AiTD/R Algorithm

The second main objective of this work was to formulate a so-called environmentally aware ML approach to AiTD/R. In general, AiTD/R algorithms consist of two major steps: first, the detection of objects in the scene and, second, classification of detected objects in the scene. Note that there are some AiTD/R algorithms that combine the detection and classification steps into one single step, and these are called one-step algorithms. However, we will focus on the two-step approach. For our purposes, the object detection step is accomplished with the edge detection algorithm described in Section 5. In summary, the CV baseline algorithm takes as an input the raw FLIR image and outputs a collection of ROIs, which may or may not contain an object. The ROIs are produced for a given raw image

by first smoothing the data using anisotropic diffusion, filtering out white noise using the shearlet transform, amplifying the edges using the Sobel operator, increasing the SNR using the bitwise AND operator, and finally performing edge detection. The ROIs are generated by using the Hough transform on the filtered image after the edge detection is performed. As described in Section 5, the computation of the ROIs can be optimized to reduce the FAR; however, this does not guarantee the reduction in false-negative rates (i.e., not detecting an object). The detection of an object using the CV baseline algorithm depends on the tuning of a series of hyperparameters, and the proper value of each hyperparameter changes from image to image due to the SNR changing over time in the thermal images.

There are two approaches to formulating an environmentally aware AiTD/R algorithm that utilizes the CV baseline algorithm to identify potential objects. The first approach is to attempt to predict the optimal hyperparameters for the CV baseline algorithm given the environmental conditions at the time the image was captured. The second approach is to inform the classification of the ROIs using an ML approach that takes both the ROI and corresponding environmental data as an input, thus providing an environmentally informed classification of the ROI. This second approach is then used as the classification step of the two-step AiTD/R algorithm. Next, we explore the first approach and discuss its disadvantages.

6.4.1 Prediction of edge detection parameters from environmental variables

The goal of this approach is to predict the optimal value of two of the key hyperparameters in the CV baseline algorithm. We will consider the anisotropic diffusion parameter κ and the Canny edge detection threshold parameter, which we call the Canny threshold. The input data for this procedure is the environmental data used to predict the contrast metrics, and the output is either the Canny threshold, κ , or a two-dimensional output consisting of both the Canny threshold and the κ parameter. To create the learning data, a baseline Canny threshold is computed based off the noise in the given image, and an optimal Canny threshold is computed by searching (linearly) for the Canny threshold that yields the best score compared to the baseline value. We use the optimal Canny threshold as the output for the ML model. As before, TabNet is used to learn the relationship between the environmental variables and the optimal Canny parameter. Figure 55a shows the predicted Canny threshold parameter using the trained TabNet model plotted against the true optimal Canny

threshold for the testing dataset. As before, the orange line in Figure 55a represents a perfect prediction. In this case, we see that the predicted Canny threshold does not accurately predict the optimal Canny threshold, evidenced by the scatter plot of the prediction versus true values not following a linear trend. In fact, if we compute a linear regression model between the true optimal Canny threshold and the predicted value, the R^2 value is 0.42, indicating the two datasets are not captured with a linear trend. Indeed, when the corresponding grades of the predicted Canny threshold are compared with the baseline Canny threshold, we see that, for about a third of the test data, the predicted Canny parameter is better than the baseline; for a third of the test data, the predicted parameter is about the same as the baseline; and for the remaining third, the predicted parameter results in a worse grade than the baseline. Qualitatively, in Figure 55b, we see that the general trend of the predicted Canny threshold parameter follows the trends of the baseline parameter and that it completely misses the outliers in the true optimal Canny threshold. Note that Figure 55b shows the comparison for a subset of the test data for the sake of visibility, but this trend is evident in the entire test dataset. Thus, there is no gain in using the predicted Canny threshold parameter from the environmental variables.

We also consider the prediction of the κ diffusion parameter, a parameter involved in the smoothing of the data, which helps to reduce the noise in the scene. Depending on the noise present in the image, the value of the optimal κ can vary substantially. As with the prediction of the Canny threshold parameter from the environmental variables, we see that the prediction of the κ diffusion parameter generally predicts values around the mean of the optimal κ and misses the outliers completely. This is clear in Figure 56, which compares the optimal κ diffusion parameter against the predicted parameter. Yet again, there is no gain in using the predicted parameter from the environmental variables.

We have found that the relationships between the best hyperparameters in the CV baseline algorithm maintain a more complex relationship with the environmental variables and that the underlying physics of the problem can be modeled with a simple deep learning approach. Note that we also explored other algorithms such as XGBoost and EvoTrees in addition to TabNet for the prediction of these hyperparameters; however, these methods proved no more fruitful than the attempt with TabNet, and the results obtained with XGBoost and EvoTrees are omitted. We now turn our

attention to a second approach in which we supplement the classification of the ROIs with the corresponding environmental metadata.

Figure 55. The predicted optimal Canny threshold plotted against (a) the true optimal Canny threshold for the testing dataset and (b) the optimal predicted and baseline Canny thresholds for a subset of the test data consisting of the first 1,000 data points.

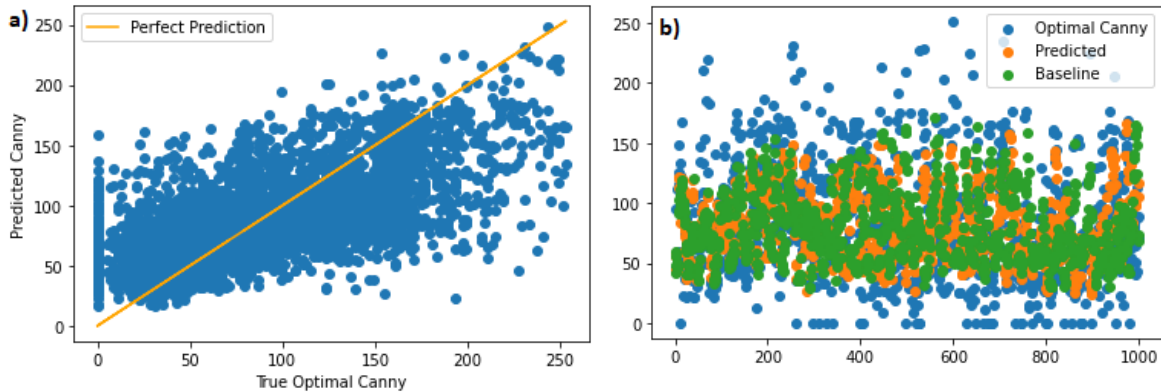
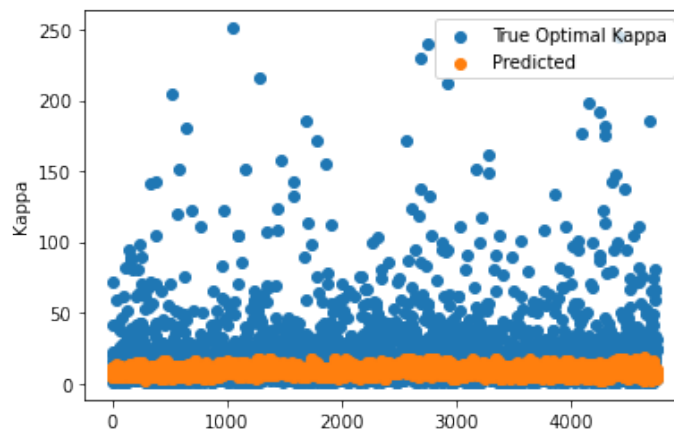


Figure 56. A comparison of the true optimal kappa diffusion parameter to the value predicted from environmental data using TabNet for the entire test dataset.



6.4.2 Environmentally informed classification of regions of interest

The second approach to incorporating environmental phenomenology into AiTD/R software involves coupling the ROIs with environmental data to classify whether the ROI contains an object. The CV baseline algorithm discussed in Section 5 produces a series of ROIs for each thermal image. To create a training dataset for the classification step of the two-step environmentally aware AiTD/R software, the test-plot data from 2018 including both before and after emplacement images is processed with the CV baseline algorithm. Further, the ROIs with potential objects are selected with a threshold that will include more potential ROIs to be classified. As

noted in Section 5, the ROIs selected to potentially contain an object are evaluated by the following assessment:

$$\text{mean}(\text{Image}) - \text{mean}(\text{ROI}) > \alpha * \sigma(\text{Image}), \quad (43)$$

where

σ = the standard deviation and

α = a threshold parameter that varies depending on the desired sensitivity in the selection of the ROIs.

For the training dataset, we use $\alpha = 0.5$ to allow for the selection of a wide variety of ROIs that both possibly contain a buried object or simply a noisy area of the image. If $\alpha = 1$, then the CV baseline algorithm is more sensitive and produces fewer ROIs, which decreases the false alarm rate at the cost of increasing the false-negative rate. The lower threshold value used for the training dataset increases the false alarm rate for the ROIs while also increasing the true positive rate as well. We can mitigate this increase in the false alarm rate by processing the ROIs through the classification algorithm to determine whether the ROI contains a buried object. From the CV baseline algorithm, each ROI is represented by the pixel corner locations in the image of the test plot. Given the top left ROI pixel location,

$$x_{\text{TL}} \in [0,115) \text{ such that } x_{\text{TL}} \in \mathbb{Z}, \quad (44)$$

$$y_{\text{TL}} \in [0,105) \text{ such that } y_{\text{TL}} \in \mathbb{Z}, \quad (45)$$

and the corresponding height and width of the ROI, we obtain the ROIs for training the classification algorithm by taking a square width, $w_{\text{sq}} = \max(h, w)$. This creates square crops of each ROI for uniformity in shape of the training data. With this, we create two-dimensional pixel arrays for the ROIs as follows:

$$\text{ROI} = [x_{\text{TL}}, x_{\text{TL}} + w_{\text{sq}}] \times [y_{\text{TL}}, y_{\text{TL}} + w_{\text{sq}}], \quad (46)$$

where, recall in Figure 38, the top left corner of the test-plot image corresponds to the pixels (0,0) and the bottom right corner corresponds to the pixels (115, 105), so the larger x pixel values correspond to a location farther to the right in the image and, similarly, the larger y pixel values correspond to a location farther to the bottom in the image. Note that if $x_{\text{TL}} +$

$w_{sq} > 115$, then we simply take $x_{TL} + w_{sq} = 115$ and similarly for the case when $y_{TL} + w_{sq}$ exceeds 105. In these cases when the square width exceeds the dimensions of the image, we produce ROIs that are not square. Then, using these pixel locations of the ROIs, we create subimage crops from the corresponding test-plot thermal image to obtain an image dataset consisting of ROIs. The resulting collection of ROI images all have various square widths or even in a small number of cases rectangular dimensions, so we transform each ROI to an equivalent size of 50×50 pixels for a uniformly sized training dataset.

After the ROIs are produced with the CV baseline algorithm, we need to create a corresponding labeled dataset for the purposes of supervised training of the classification algorithm. We define the label, l , of an ROI as follows:

$$l(\text{ROI}) = \begin{cases} 1 & \text{if } \text{ROI} \cap \Omega \neq \emptyset \\ 0 & \text{if } \text{ROI} \cap \Omega = \emptyset \end{cases} \quad (47)$$

where ROI is the two-dimensional array of pixel locations, as described above, and Ω is a set that consists of four two-dimensional arrays of pixel locations for each object:

$$\Omega = \{\text{SP}, \text{SM}, \text{DM}, \text{DP}\} \quad (48)$$

for $\text{SP} = [90,110] \times [85,105]$, $\text{SM} = [10,30] \times [85,105]$, $\text{DM} = [90,110] \times [5,25]$, and $\text{DP} = [10,30] \times [5,25]$. Figure 57 shows an example test-plot image processed by the CV baseline algorithm and the corresponding ROI crops with their labels prior to the transformation step. This sample image provides a scenario in which the ROIs detect all four objects, but there are also two ROIs corresponding to locations known to not have an object. The classification step of the ATR algorithm can determine which of these ROIs does indeed contain an object.

Lastly, to prepare the training dataset for the environmentally informed classification algorithm, we need to prepare environmental metadata for each ROI. Each ROI has a corresponding timestamp, which can be matched to the iid environmental data. Using the analysis of the environmental data importance from the previous section, a subset of the iid environmental variables is used: the soil moisture content, average air temperature, incoming solar radiation, average relative humidity, and

average pressure. Table 9 shows the environmental metadata corresponding to the example image in Figure 57.

Figure 57. An example of a thermal image processed with the computer vision algorithm and the resulting ROIs. Each ROI is labeled as “yes” if it contains a buried object and “no” if it does not contain an object, and this labeled data is used to train the classification algorithm. This thermal image was captured 19 September 2018 at 2145.

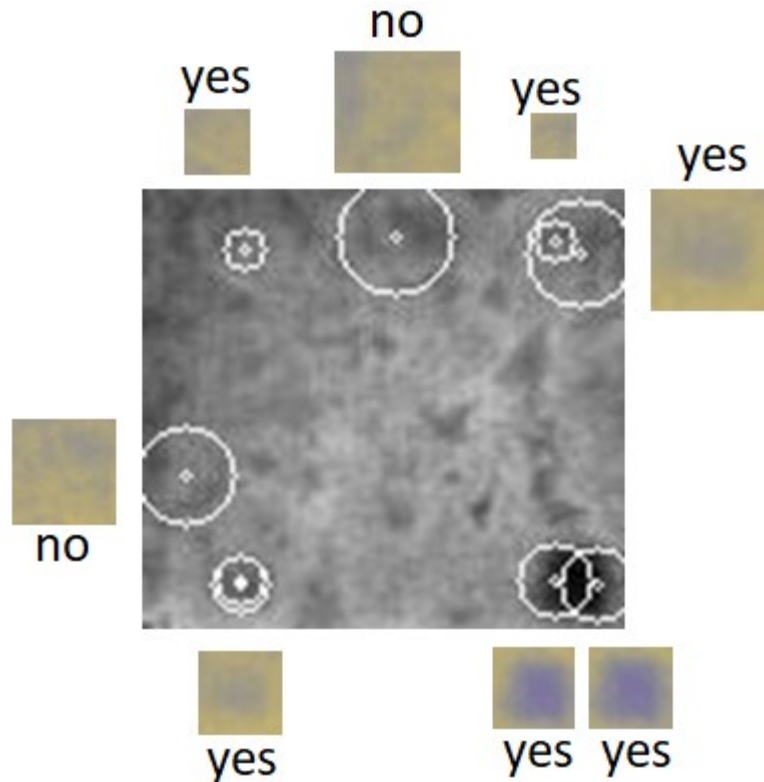


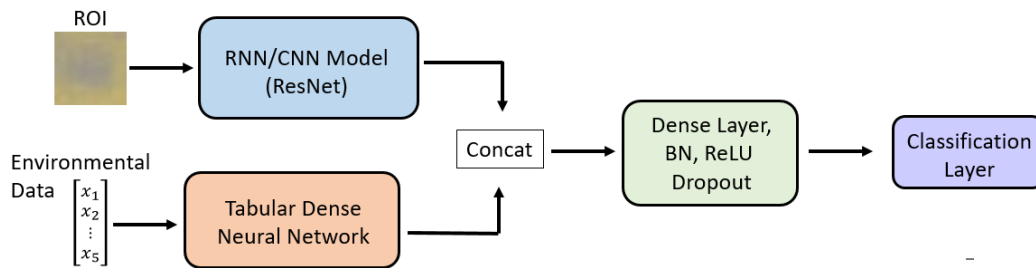
Table 9. Environmental metadata corresponding to the example thermal image in Fig. 57.

Environmental Variable	Value for 19 September 2018 at 2145
Soil Moisture Content (%)	0.164462
Average Air Temperature (°C)	11.99
Incoming Solar Radiation (W/m ²)	-6.488
Average Relative Humidity (%)	92.55
Average Pressure (mbar)	1002.5

For the classification step of the two-step ATR algorithm, we use a framework inspired by Gessert et al. (2020), which couples metadata with images to produce a more accurate classification. In the paper by Gessert et al. (2020), classifying images of skin lesions coupled with patient

metadata increased the accuracy of the classification algorithm. In particular, they use a dense neural network to process the tabular metadata and a convolutional neural network to process the image data, then couple the results to produce a classification. We utilize this same framework for our environmentally informed approach to classifying the ROIs. Figure 58 shows the architecture we use, which is directly inspired by Gessert et al. (2020).

Figure 58. The architecture for the environmentally informed classification algorithm to process and classify the ROIs. This architecture is directly inspired by the work in Gessert et al. (2020).



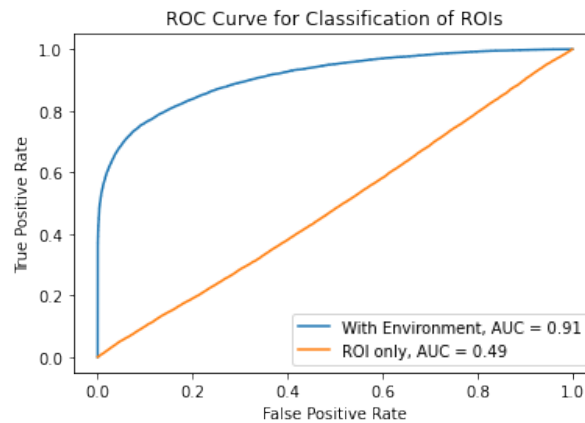
We utilize ResNet34 to process the ROIs, which is a residual neural network introduced in He et al. (2016), and implement this algorithm by using the fastai deep learning library (Howard and Gugger 2020). In the fastai library, we use the ResNet34 algorithm, which has been pretrained on the ImageNet dataset for faster training and learning (Stanford Vision Lab 2021). In the fastai framework, custom neural networks can also be constructed; and for the tabular dense neural-network block, we define a dense neural network with batch normalization, the ReLU activation function, and a dropout step, as Gessert et al. (2020) did, to avoid overfitting.

To train the neural network, as before, we divide the dataset into a training set, validation set, and a testing set. The full ROI dataset consists of more than 200,000 ROI crops computed from the approximately 47,000 images taken from May to November 2018. For comparison, we classify the images using solely ResNet34 and compare with the classification using the framework shown in Figure 59. We assess the results using a ROC curve computed for the testing dataset, which is unseen to the model during training. By incorporating the environmental metadata into the classification algorithm, we greatly increase the accuracy in the classification of the ROIs. The results in Figure 59 capture the error in only the classification step of the AiTD/R algorithm and does not capture the error in the identification of objects via the CV algorithm and computation of the ROIs.

However, the results in Figure 59 do indicate that we can very reliably determine whether the ROI contains a buried object once an ROI is detected with the CV algorithm.

Next, to gain a better understanding of the error in the ROI detection, we compare the contrast metrics and environmental condition distributions for when the ROIs detect each object.

Figure 59. The receiver operating characteristic curves for classification of ROIs comparing the ResNet34 classification to the environmentally informed classification.

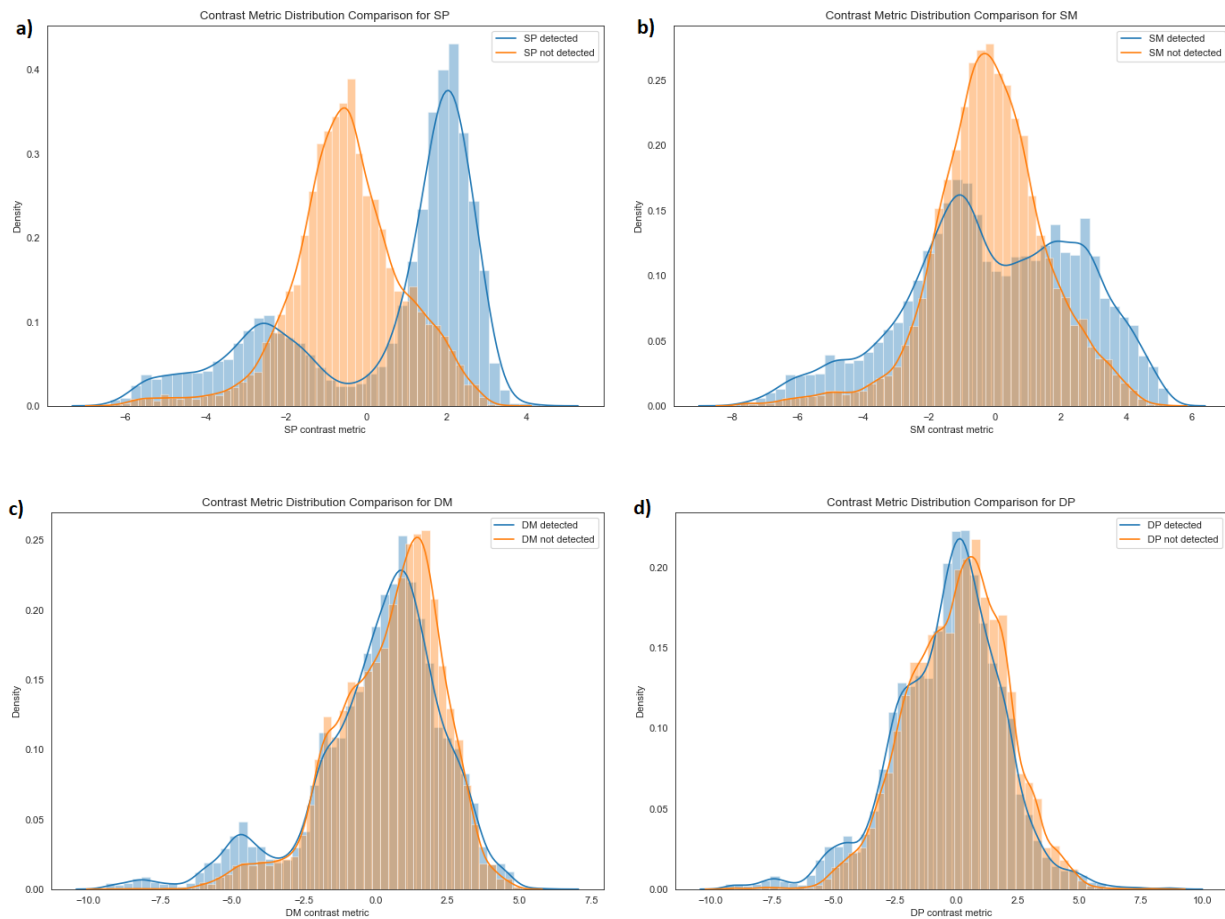


6.4.3 Analysis of ROI detection with contrast metrics and environmental conditions

In this section, to gain some insight into when the objects can be detected, we compare the contrast-metric distributions for when the ROIs detect a given buried object. We will also consider the distributions for the soil water content and the time of day. In this section, we look at the contrast-metric distributions for when the ROIs detect the SP, SM, DM, and DP object individually (Figure 60). For the SP object in Figure 60a, we see a clear separation in the distribution for when the ROIs detect the SP object, which indicates that the baseline approach for formulating the ROIs works well for the SP object. However, for the SM, DM, and DP objects in Figure 60b–d, the contrast-metric distribution does not show as clear of a distinction. For the SM object, there is a separation for the larger positive contrast-metric values, indicating this object is easier to detect for this range of contrast metrics; however, overall, there is a large overlap in the distributions, indicating the baseline CV approach may need to be improved for the SM object. Like the SM object, the contrast-metric distributions for the

DP and DM objects show substantial overlap, indicating it is difficult to separate out these objects from the background noise in the scene.

Figure 60. A comparison of contrast-metric distributions when the ROIs detect and do not detect a given object: (a) SP object with the SP contrast metric, (b) SM object with SM contrast metric, (c) DM object with DM contrast metric, and (d) DP object with DP contrast metric.

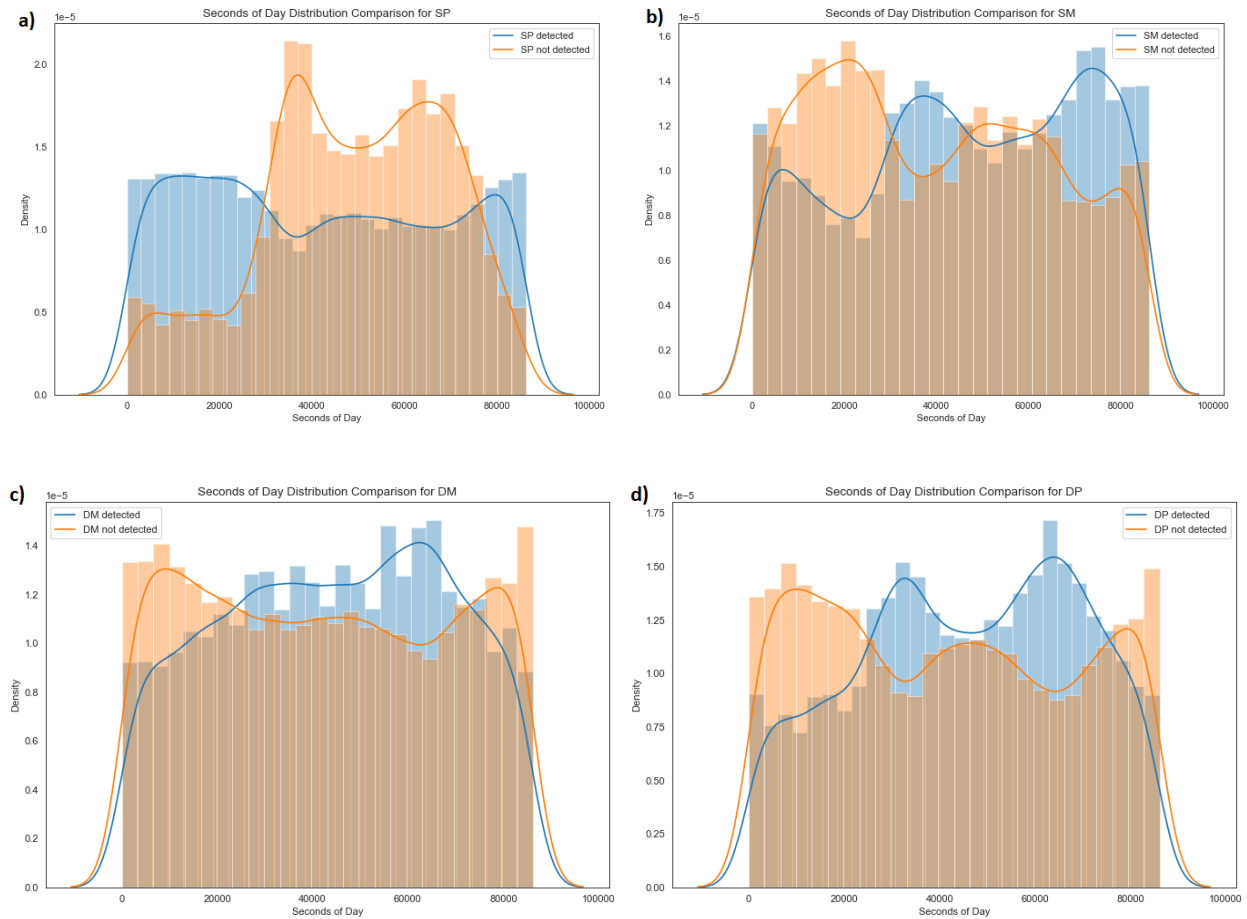


We also consider the time of day the image was taken and how this affects the ability to detect the objects with ROIs shown in Figure 61. We compute the time of day by seconds of the day where 0000 corresponds to 0 seconds. All four objects indicate that the time of day plays a role in the ability to detect the objects with the ROIs. For the SP object, it is most easily detected in the early morning and late evening and less detectable in the middle of the day when the solar radiation brings the object to thermal equilibrium with the surrounding soil.

In contrast, the SM object is difficult to detect from 0000 to about 0800 and in the middle of the day when the soil and object have reached

thermal equilibrium, otherwise the object is relatively detectable via the ROIs. In contrast, the two deep objects are most easily detected in the middle of the day as shown by Figure 61c and d. As a future effort of this work, we could couple this information with the AiTD/R by reporting a measure of the reliability of the AiTD/R to detect the different buried-object types given the time of day and environmental conditions.

Figure 61. A comparison of the time-of-day distributions for when the ROIs detect and do not detect a given object: (a) SP object, (b) SM object, (c) DM object, and (d) DP object.



7 Conclusions and Recommendations

7.1 Conclusions

The present study focused on identifying the environmental phenomenological variables contributing to either enhancement or degradation of the ability to detect buried objects. Once identified, the secondary objective was to develop techniques to improve the performance of AiTD/R software.

To identify the predominant environmental phenomenological parameters affecting object detection, we took several different approaches: (1) multilevel statistical modeling, (2) direct image analysis, (3) physics-based thermal modeling, and (4) application of ML techniques. We used these different techniques both to check the others and to inform the analysis with a particular method.

Multilevel modeling indicated surface-temperature response above the SP object produced the highest temperature variance and spatial temperature variability at midafternoon. The variance and deviation patterns approximately followed shortwave IR or shortwave reflectance response except on rainy and cloudy days. In these cases, precipitation events resulted in a uniform surface-soil temperature, precluding subsurface object detection. Consequently, the best time for detecting subsurface targets was when the soil had a low soil moisture content. Even though these periods exhibited high surface-soil-temperature variance, the magnitude of the surface-temperature response above a buried target was sufficiently large to overcome the background noise. This thermal background noise appears to be a function of slight differences in soil topography. Elevation differences at the centimeter scale were sufficient to introduce surface-soil-temperature variability (i.e., speckled pattern). However, the slope or inclination of the ground surface had no relation to surface-soil-temperature spatial variability. Finally, the ground aspect and orientation relative to incoming solar radiation appears to be the primary factor in creating background thermal noise. Warmer days resulted in a more pronounced surface-soil-temperature response and temperature variance, especially for the SP object, than the background and other buried objects. Air, surface soil, and surface-soil temperature as a function of time of year had little to no impact on the ability to detect the subsurface targets.

We used a variety of metrics to assess the visibility of the buried objects as a function of difference in surface-soil temperatures between the object

and background locations. Consistent with our earlier work (Clausen, Dorvee, et al. 2020; Clausen, Musty et al. 2020; Clausen et al. 2021, 2022; Workman and Clausen 2019), incoming solar radiation was the dominant factor impacting object visibility using thermal IR. Higher incoming solar radiation levels resulted in improved object detectability. For the plastic objects, relative humidity was the next most important factor followed by air temperature and wind speed. Increasing atmospheric humidity resulted in decreased object visibility while higher air temperature corresponded with increased visibility. Conversely, increased wind speeds deteriorated object visibility. For the metal targets, relative humidity was the second most important variable affecting object visibility. Precipitation events, which also correspond to increased soil moisture levels, resulted in a uniform spatial distribution of surface-soil temperatures, masking the presence of subsurface objects.

Our earlier work (Clausen et al. 2022) converted thermal IR radiance values to temperature. Thermal modeling (Trautz et al. 2022 in press) indicates there is a good match between measured and model simulated values, but it appears that the measured IR radiance values when converted to temperature are less accurate at low temperatures.* The model underestimates the object's temperature (the object is colder than measured temperatures). The model indicates the thermal variance difference between the object and background is less during periods of low air temperatures. Consequently, buried-object visibility is degraded with decreasing air and soil temperatures. Still, at the CRREL test site in Hanover, New Hampshire, the best time of day for detecting the buried objects regardless of season was early in the morning.

In addition, we developed an approach using a Canny edge methodology to identify regions of interest potentially harboring a target object. The first step in the process is the conversion of thermal radiance values to U8 data. The data from the entire image, ROI, is then smoothed using anisotropic diffusion, filtered using a shearlet transformation to remove salt-and-pepper noise, followed by amplification of the edges using a Sobel operator, and increasing the SNR with a bitwise AND operator. Finally, the Canny edge detection function is applied. The complete process is a multistage algorithm that first reduces the noise, followed by localizing the intensity

* A.C. Trautz, R. Kala, S.E. Howington, M. Bray and M.W. Farthing, "Model Development, Calibration, and Validation for Support of Remote Thermal Detection of Buried Objects Research" (unpublished manuscript, 2022), Microsoft Word file.

gradients and nonmaximum suppression, and concludes with hysteresis thresholding. Our CV prototype is effective at finding targets that are semi-obscured to the naked eye. The CV prototype can be used as a stand-alone process or in conjunction with ML techniques considering the environmental phenomenology.

Finally, the CV technique utilizing Canny edge detection is coupled to an environmental phenomenology ML preprocessor. The ML preprocess object variables and contrast metrics to define the ROI. After analyzing a variety of contrast metrics, we selected the best and combined them through PCA to obtain a single contrast metric. Next, we used an ML algorithm to model the nonlinear relationship between the environmental variables and object variables. We performed the analysis using a boosted trees algorithm called EvoTrees paired with Shapley analysis to establish the relationship between environmental variables. Then, the gradient-boosted trees method is applied to two categories of contrast metrics: the PCA contrast metric for all objects and the PCA contrast metric for the SP object. After optimizing the hyperparameters for the boosted trees model, it is trained using the training and validation subsets of the environmental variables and the selected contrast metrics. The boosted trees ML model learned the relationship between the environmental variables and the PCA contrast metric for all four objects relatively well, indicated by the small value of the error metrics in both the testing and training data. The four most important environmental variables in the formation of the ML model are incoming solar radiation, soil water content, average air temperature, and average relative humidity. These are the same variables of importance identified through multilevel statistical modeling and thermal modeling. Incoming and reflected solar radiation both have a positive effect on the ML model whereas atmospheric air pressure, air temperature, and soil water content have a negative effect. The environmental variables with a mean positive effect generally aid in the prediction of the contrast metric, while the environmental variables with a mean negative effect make it more difficult to accurately predict the contrast metric. The SP object was the most distinguishable from the background thermal noise whereas the deep objects were relatively difficult to distinguish from the noise. Our single contrast metric for metal objects indicates that it was more difficult to detect metal than plastic objects. The environmental phenomenological ML algorithm coupled to standard AiTD/R methods improved performance by 50%.

7.2 Recommendations

For future studies, we recommend further validating the conversion of thermal IR imagery radiance values to temperatures during periods of lower air temperatures. At first, it might appear that the model is not accurate at low temperatures, but the conclusion from this modeling effort is that the imagery conversion from radiance values to temperature is most likely why it is not matching as well at low temperatures. The simulations using the soil-temperature measurements as the top boundary condition indicate a better fit than when the thermal-imagery temperature is used as the forcing temperatures. We also recommend using more temperature sensors at the surface so that the thermal-imagery conversion can be validated. Rather than converting the thermal IR images to temperature, a better way forward would be to perform future analysis on the radiance values.

The ML object-recognition effort introduced a new approach to incorporating the environmental phenomenology for the classification of buried objects in thermal images. In the design of a two-step AiTD/R algorithm in which one step is the detection of regions of interest and the second step is the classification of these regions, the environmentally informed approach fits in as this second step. There is room for improvement in the proposed approach, namely, we can implement the environmentally informed approach with other common algorithms used for object detection and classification, such as Faster R-CNN or other deep convolutional neural-network architectures (Ren et al. 2017; Nasrabadi 2019). An algorithm such as Faster R-CNN could be used for both the detection of ROIs and the classification of ROIs. As noted, in our work, there is an inherent error in the ROI detection rate, as shown with the distributions considered in the previous section. We can greatly improve the accuracy of the overall two-step algorithm, decreasing the false-negative rate in the ROI detection using Faster R-CNN. One possible approach would be to incorporate the environmental conditions in the tuning of the hyperparameters in the CV baseline algorithm for optimal object detection with the ROIs. Further, the two-step AiTD/R discussed here could be paired with a so-called reliability measure that would utilize factors such as the time of day, incoming solar radiation, approximate soil water content, and the contrast-metric value to indicate the trustworthiness of the analysis for buried objects in each thermal image with these conditions. We plan to implement these recommendations during our work in the upcoming year.

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Appendix A: Topographic Characteristics Frequency Distribution Summary

Figure A-1. Elevation (*left graphs*), aspect categories (*center graphs*), and slope in degrees (*right graphs*) frequency distribution for each of the 10 × 10 cells grid samples. Tmp11 is DM; Tmp13 is SP; Tmp19 is SM; Tmp33 is DP. (Tmp11, Tmp13, Tmp19, and Tmp33 are located 5 cm bgs above DM, SP, SM, and DP objects, respectively.)

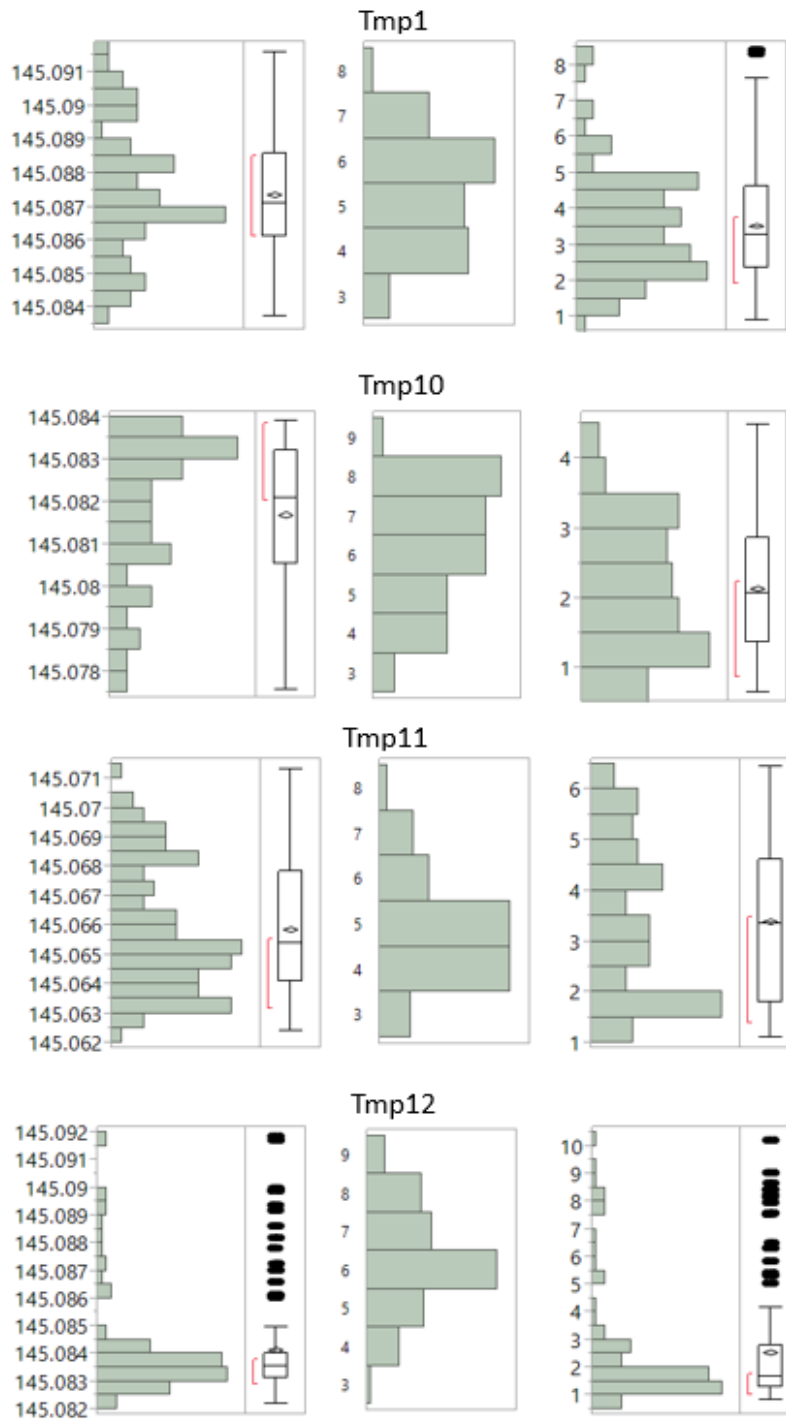


Figure A-1 (cont.). Elevation (*left graphs*), aspect categories (*center graphs*) and slope in degrees (*right graphs*) frequency distribution for each of the 10 × 10 cells grid samples. Tmp11 is DM; Tmp13 is SP; Tmp19 is SM; Tmp33 is DP. (Tmp11, Tmp13, Tmp19, and Tmp33 are located 5 cm bgs above DM, SP, SM, and DP objects, respectively.)

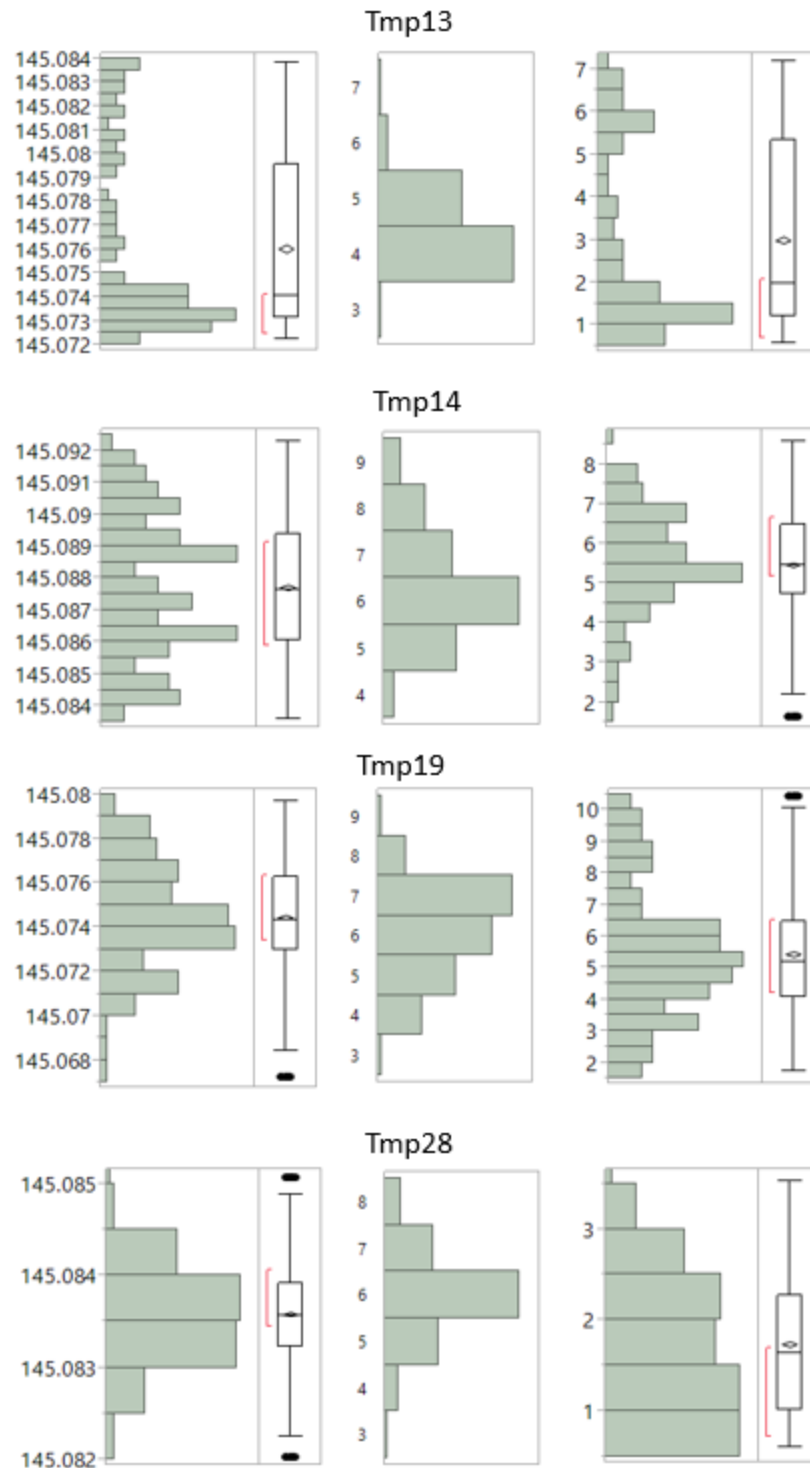
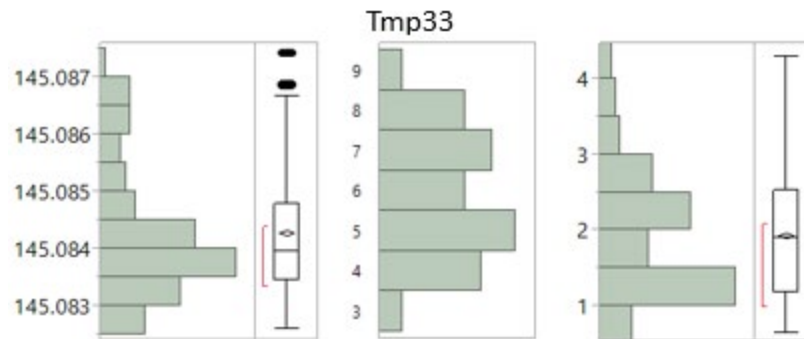


Figure A-1 (cont.). Elevation (*left graphs*), aspect categories (*center graphs*) and slope in degrees (*right graphs*) frequency distribution for each of the 10×10 cells grid samples. Tmp11 is DM; Tmp13 is SP; Tmp19 is SM; Tmp33 is DP. (Tmp11, Tmp13, Tmp19, and Tmp33 are located 5 cm bgs above DM, SP, SM, and DP objects respectively.)



Appendix B: Hourly Summary of Mean Soil Surface Temperature Using One- Way ANOVA

Figure B-1. Hourly IR temperature mean between locations at times 0100–0400 (*top left, bottom left, top right, and bottom right, respectively*). Tmp11 is DM; Tmp13 is SP; Tmp19 is SM; Tmp33 is DP. The vertical axis represents the overall hourly mean temperature distribution, and the horizontal axis represents the temperature probe identification and location. The *green bar* is the data median, the *bottom blue bar* is the estimated 25% point, the *top blue bar* is the estimated 75% point, and the *vertical gray bars* represent the magnitude of the interquartile range difference.

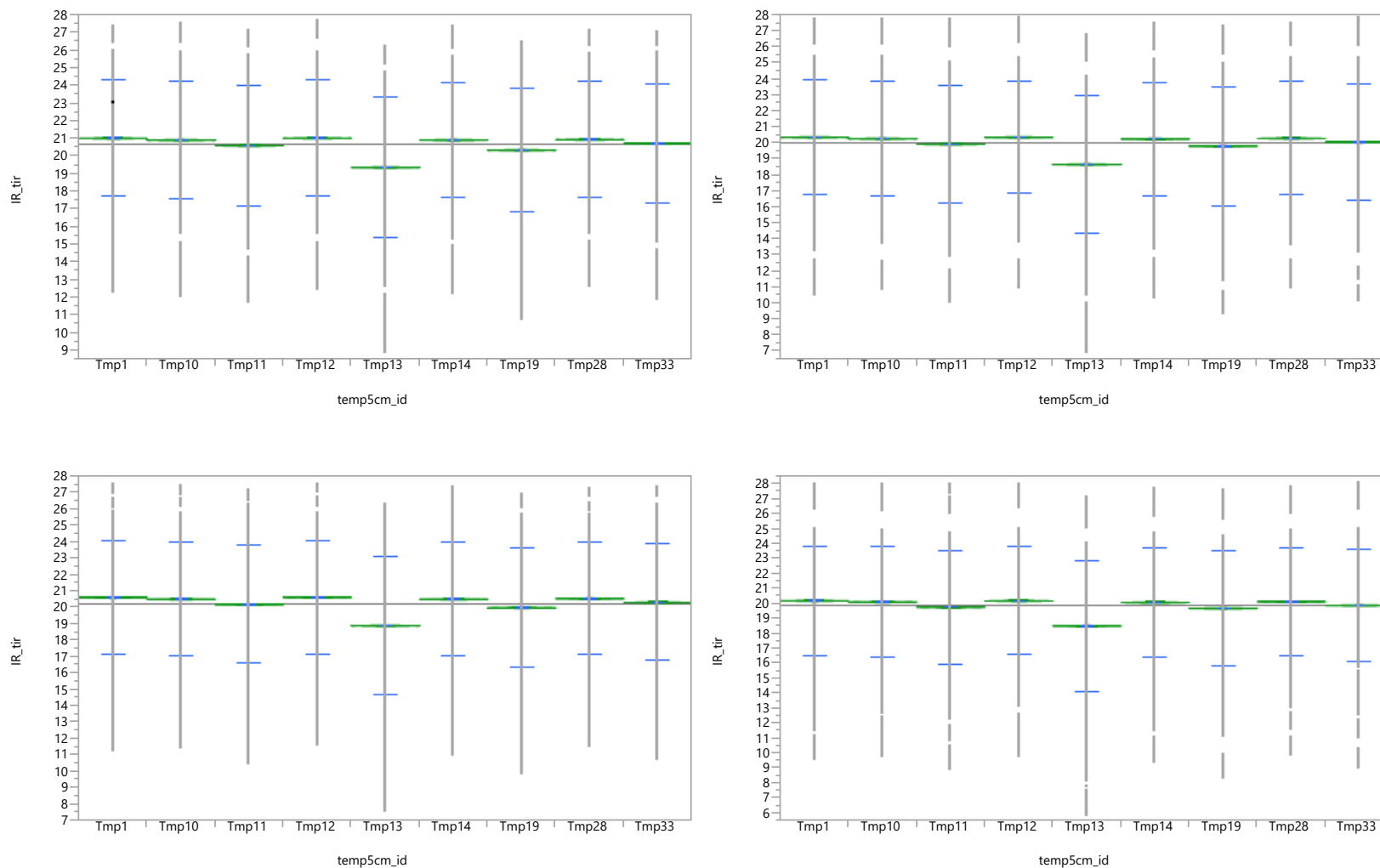


Figure B-2. Hourly IR temperature mean between locations at time 0500–0800 (*top left, bottom left, top right, and bottom right, respectively*).
 Tmp11 is DM; Tmp13 is SP; Tmp19 is SM; Tmp33 is DP.

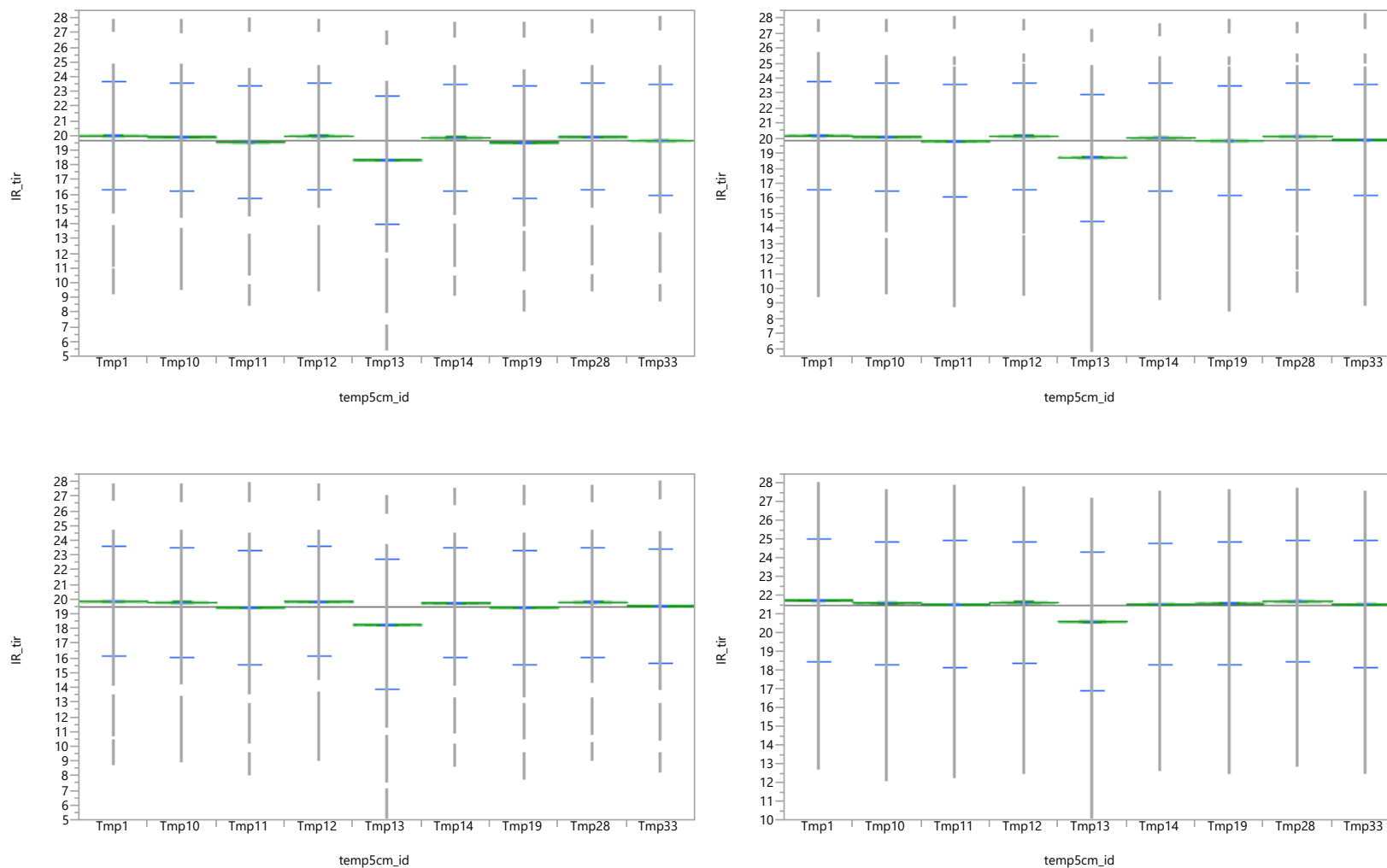


Figure B-3. Hourly IR temperature mean between locations at time 0900–1200 (*top left, bottom left, top right, and bottom right, respectively*).
 Tmp11 is DM; Tmp13 is SP; Tmp19 is SM; Tmp33 is DP.

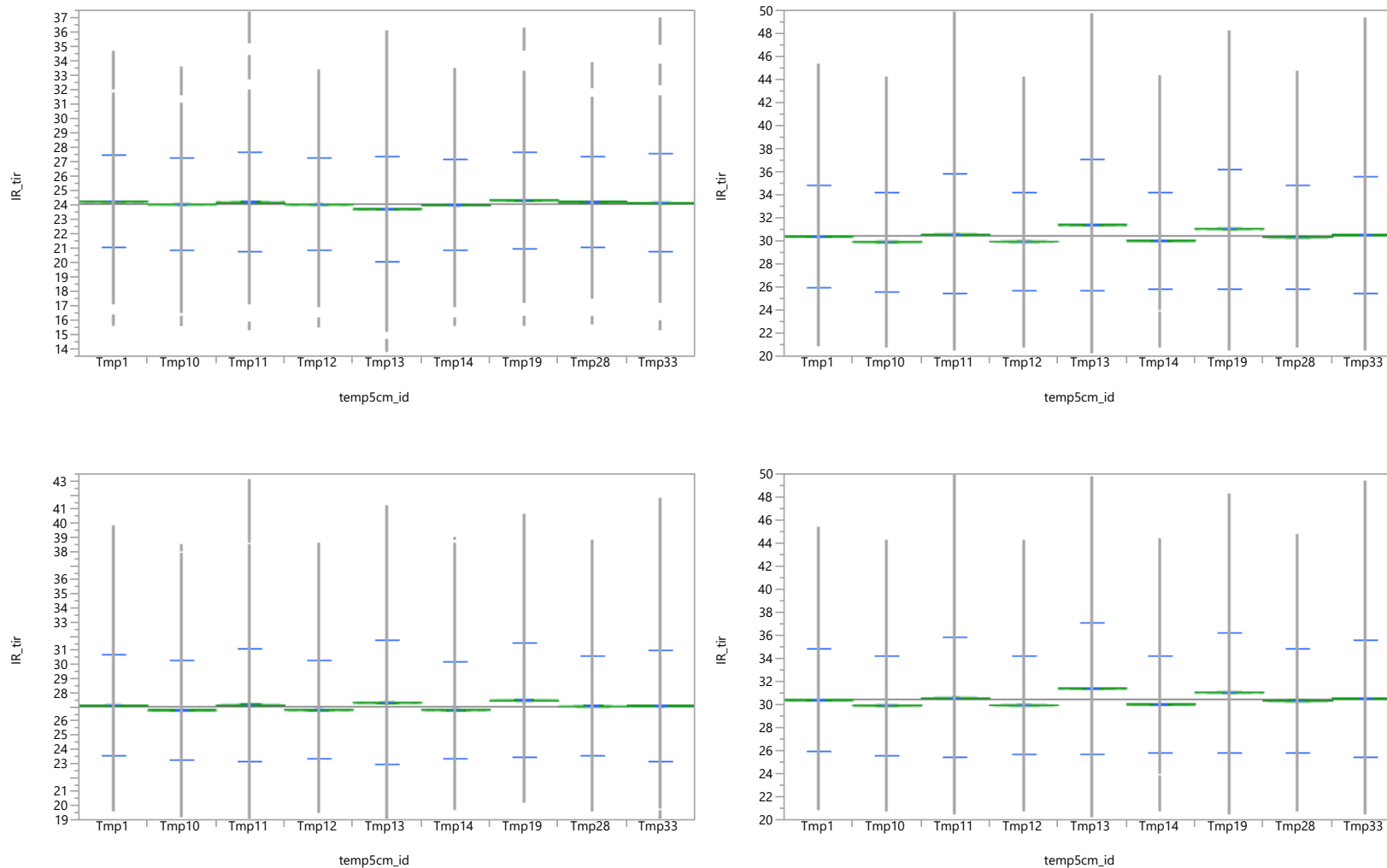


Figure B-4. Hourly IR temperature mean between locations at time 1300–1600 (*top left, bottom left, top right, and bottom right, respectively*).
 Tmp11 is DM; Tmp13 is SP; Tmp19 is SM; Tmp33 is DP.

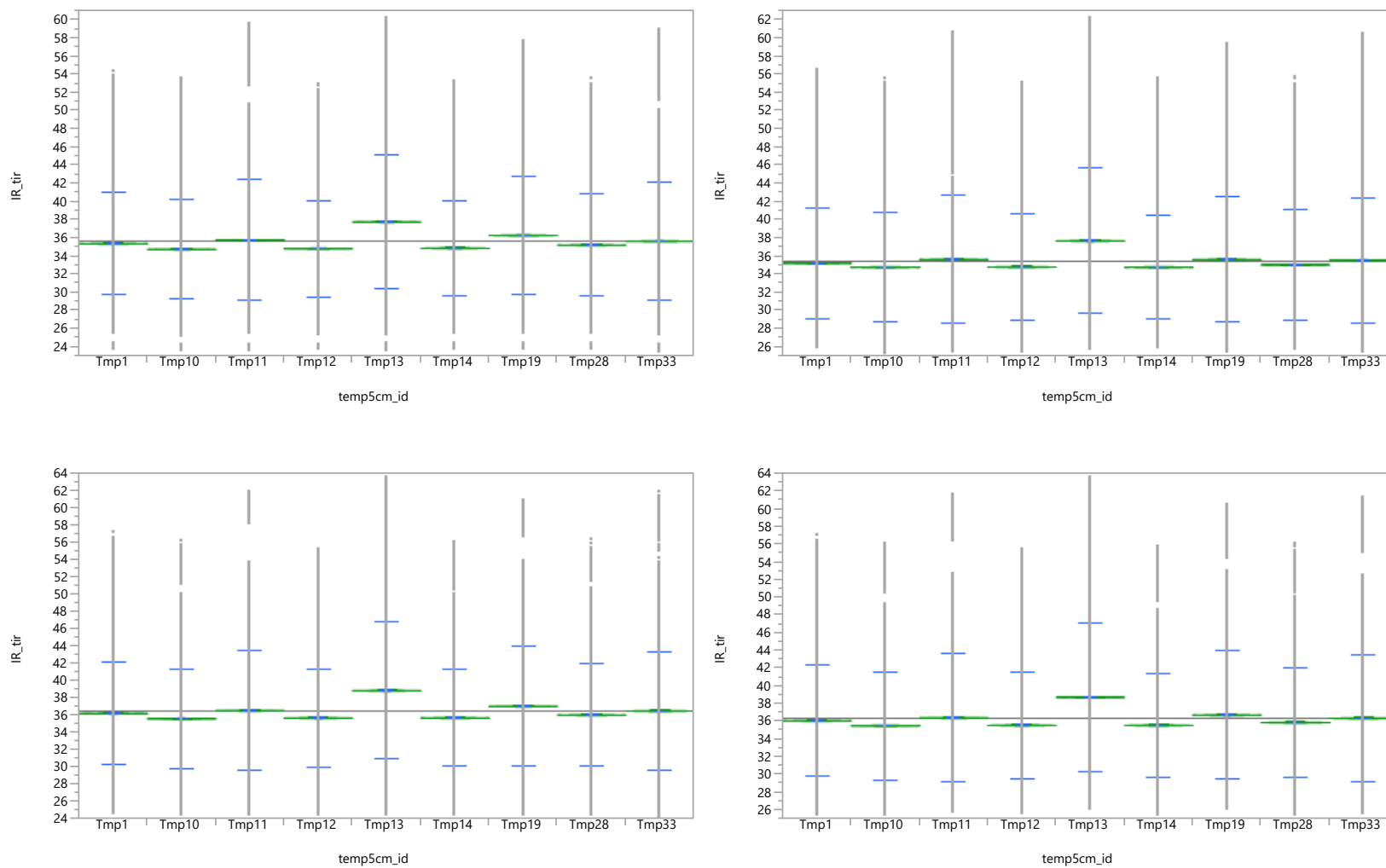


Figure B-5. Hourly IR temperature mean between locations at time 1700–2000 (*top left, bottom left, top right, and bottom right, respectively*).
 Tmp11 is DM; Tmp13 is SP; Tmp19 is SM; Tmp33 is DP.

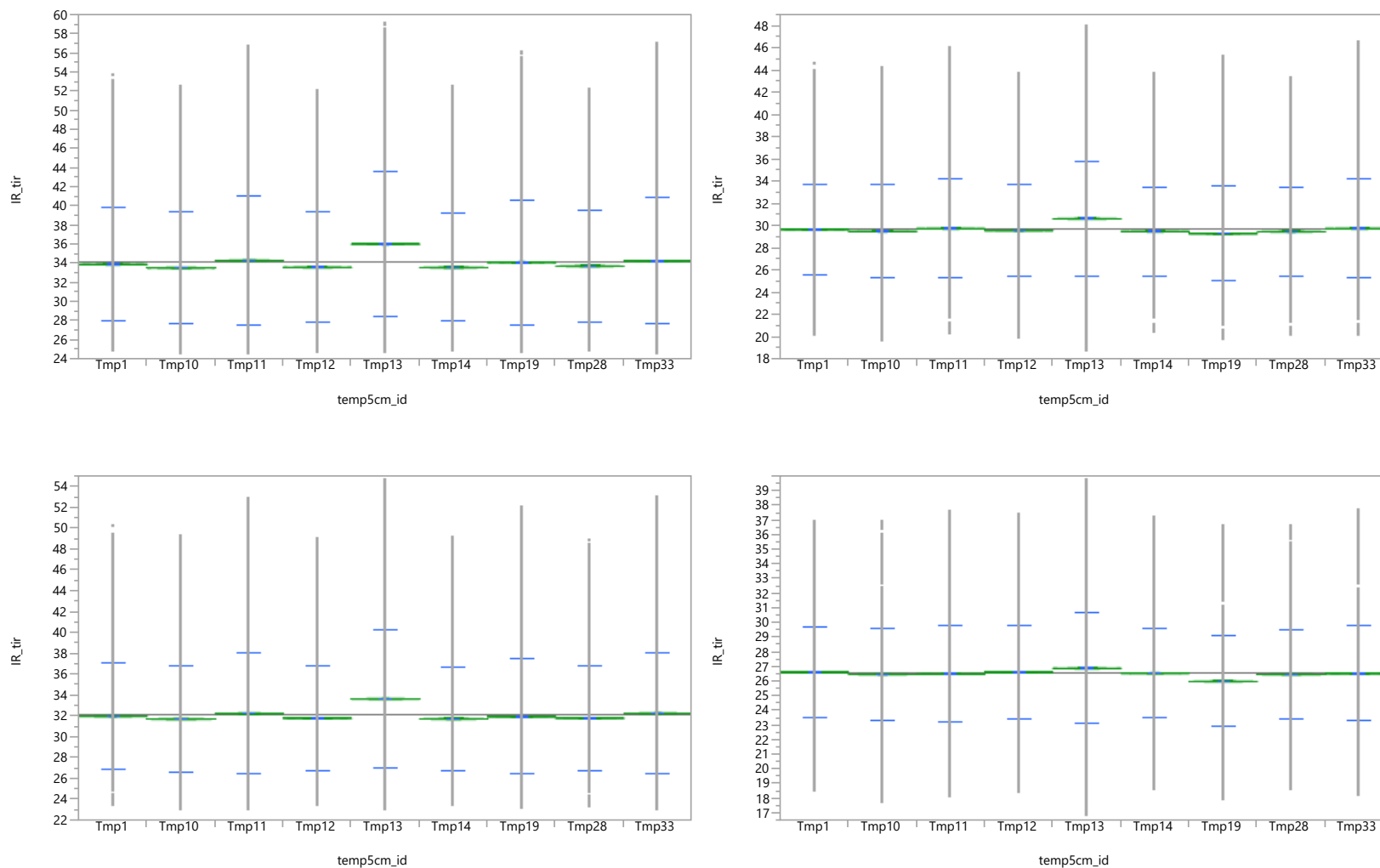
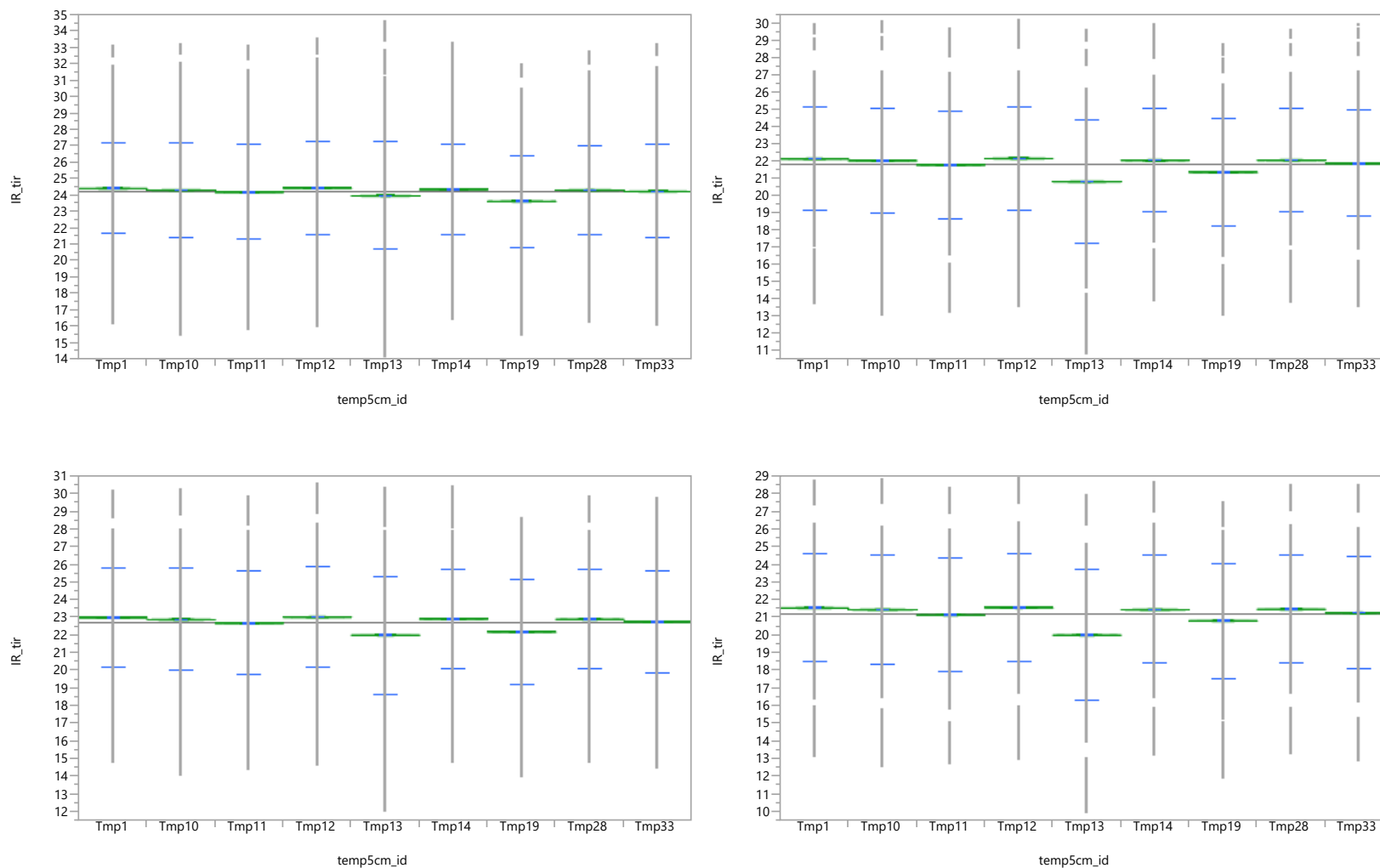


Figure B-6. Hourly IR temperature mean between locations at time 2100–2400 (*top left, bottom left, top right, and bottom right, respectively*).
 Tmp11 is DM; Tmp13 is SP; Tmp19 is SM; Tmp33 is DP.



Appendix C: Test Bed Result Data Tables

Table C-1. TMP1 (background) correlations and parameter estimates between soil temperature derived by thermal IR, elevation, and aspect with statistical significance, including an hourly summary of environmental variables and soil temperature derived by thermal IR.

Date	Time	Environment Variables			Correlation and Parameter Estimates						Soil Temperature (°C)				
		Air Temp. (°C)	Rh (%)	SWR (W/m ²)	R ²	Warmest Aspect Orientation	South-Southeast Aspect Scaled Coef.	Intercept β_a for Southeast Aspect	β_b Temp. Change	Temp. (Δ /1 cm)	Mean	Min	Max	Std Dev	Var
8/7/2018	13	31.0	58	110	0.22			40.55	-1.31	-1.66	39.78	38.87	42.49	0.775	0.601
8/7/2018	12	29.7	61	113	0.26			39.11	-1.01	-1.28	38.54	37.82	40.54	0.530	0.281
8/7/2018	15	31.4	50	71	0.21			38.46	-1.00	-1.27	37.85	36.97	39.98	0.614	0.377
8/25/2018	15	27.4	49	95	0.20			38.03	-0.96	-1.22	37.57	36.65	39.28	0.548	0.301
8/6/2018	15	32.8	44	114	0.25			41.55	-0.89	-1.13	41.05	40.44	42.73	0.479	0.229
8/31/2018	11	19.6	65	83	0.29			30.24	-0.79	-1.00	29.88	29.29	31.14	0.375	0.141
8/26/2018	11	22.1	68	79	0.31			31.50	-0.78	-0.99	31.15	30.51	32.24	0.368	0.135
8/6/2018	14	32.0	52	115	0.22			41.86	-0.71	-0.90	41.44	40.69	42.84	0.411	0.169
8/25/2018	13	24.8	66	85	0.33			35.23	-0.70	-0.89	34.93	34.37	36.09	0.332	0.111
7/29/2018	11	23.2	57	110	0.34	NE, W	0.19**	31.64	-0.68	-0.86	31.26	30.70	32.17	0.316	0.100
8/25/2018	14	25.6	57	46	0.34	NE		34.00	-0.67	-0.85	33.71	33.16	34.76	0.308	0.095
8/24/2018	14	26.1	51	91	0.34	NE		35.88	-0.66	-0.84	35.64	34.97	36.89	0.353	0.125
7/29/2018	15	25.6	46	103	0.23	NE, W		34.62	-0.66	-0.84	34.26	33.84	35.41	0.350	0.123
8/7/2018	11	28.3	66	106	0.29		0.17***	36.51	-0.65	-0.82	36.11	35.49	37.29	0.328	0.107
7/29/2018	14	24.9	50	116	0.24	NE, W		34.80	-0.62	-0.78	34.45	33.91	35.57	0.339	0.115
8/24/2018	13	24.3	57	94	0.38	NE		35.49	-0.61	-0.77	35.25	34.39	36.10	0.301	0.091
8/6/2018	12	28.4	65	119	0.37	NE, SW	0.17**	38.46	-0.59	-0.75	38.11	37.53	38.95	0.271	0.074

* $p < 0.001$; ** $p < 0.01$; *** $p < 0.05$; Temp. = temperature; Rh = relative humidity; SWR = shortwave reflectance; Coef. = coefficient; SE = standard error; Min = minimum; Max = maximum; Std Dev = standard deviation; Var = variance.

Table C-2. TMP10 (background) correlations and parameter estimates between soil temperature derived by thermal infrared (IR), elevation, and aspect with statistical significance, including an hourly summary of environmental variables and soil temperature derived by thermal IR.

Date	Time	Environment Variables			Correlation and Parameter Estimates							Soil Temperature (°C)				
		Air Temp. (°C)	Rh (%)	SWR (W/m ²)	R ²	Warmest Aspect Orientation	South-Southeast Aspect Scaled Coef.	West-Southwest Aspect Scaled Coef.	Intercept β_a for Southeast Aspect	β_b Temp. Change	Temp. (Δ /1 cm)	Mean	Min	Max	Std Dev	Var
8/27/2018	15	29.3	51	79	0.51	W	0.47**	0.53*	39.59	1.38	2.19	41.58	40.13	42.86	0.578	0.335
8/26/2018	14	26.7	55	94	0.53	W	0.42**	0.52*	37.36	1.24	1.97	38.98	37.83	40.08	0.406	0.164
8/27/2018	14	28.4	54	74	0.50	W	0.36**	0.44*	38.35	1.12	1.78	40.00	38.77	41.39	0.562	0.316
8/26/2018	13	25.4	57	98	0.53	W	0.48*	0.48*	36.04	1.07	1.70	37.51	35.99	39.45	0.708	0.501
8/31/2018	15	23.0	53	60	0.54	W		0.34*	32.62	1.03	1.63	34.09	33.01	35.21	0.424	0.180
8/24/2018	13	24.3	57	94	0.59	W	0.34**	0.24**	33.72	0.94	1.49	35.25	34.39	36.10	0.301	0.091
8/24/2018	14	26.1	51	91	0.56	W	0.38**	0.23**	34.25	0.92	1.46	35.64	34.97	36.89	0.353	0.125
8/31/2018	12	21.5	56	81	0.55	W	0.30**	0.32**	31.05	0.92	1.46	32.36	31.13	34.17	0.610	0.372
8/31/2018	13	22.3	54	74	0.53	W	0.24**	0.32*	32.66	0.91	1.44	34.05	33.05	35.35	0.472	0.223
8/26/2018	15	26.1	58	43	0.55	W	0.27**	0.33*	34.39	0.89	1.41	35.48	34.63	36.20	0.312	0.097
8/24/2018	12	21.9	63	91	0.60	W	0.33**	0.22**	30.87	0.88	1.40	32.29	31.46	32.83	0.249	0.062
8/20/2018	12	22.1	69	89	0.60	W	0.39*	0.27*	32.16	0.87	1.38	33.62	33.03	34.25	0.236	0.056
8/24/2018	11	19.2	69	81	0.57	W	0.30**	0.23**	26.85	0.85	1.35	28.13	27.32	28.53	0.216	0.047
8/24/2018	15	26.9	52	83	0.58	W	0.34**	0.25**	34.16	0.83	1.32	35.48	34.59	36.78	0.399	0.159
8/25/2018	15	27.4	49	95	0.58	W	0.40*	0.35*	36.38	0.81	1.29	37.57	36.65	39.28	0.548	0.301
8/20/2018	14	24.0	54	62	0.61	W	0.31**	0.20**	32.46	0.80	1.27	33.77	33.17	34.45	0.245	0.060
8/20/2018	15	24.9	45	74	0.58	W	0.35*	0.18**	31.89	0.79	1.25	33.09	32.48	34.05	0.326	0.106
8/6/2018	15	32.8	44	114	0.21	NW		0.21**	39.62	0.78	1.24	41.05	40.44	42.73	0.479	0.229
8/20/2018	11	18.5	82	78	0.60	W	0.32*	0.20**	26.26	0.77	1.22	27.51	27.13	27.79	0.147	0.022
8/27/2018	13	27.1	59	55	0.57	W	0.28*	0.29*	35.58	0.75	1.19	36.60	35.34	38.03	0.565	0.320
8/31/2018	14	22.2	55	44	0.53	W		0.25*	30.75	0.75	1.19	31.85	30.95	32.81	0.337	0.113
8/20/2018	13	23.2	60	63	0.59	W	0.31**	0.18**	32.43	0.74	1.17	33.72	33.19	34.35	0.234	0.055
8/26/2018	12	23.8	63	85	0.60	W	0.37*	0.28*	33.66	0.73	1.16	34.56	33.46	36.27	0.572	0.327

Date	Time	Environment Variables			Correlation and Parameter Estimates							Soil Temperature (°C)				
		Air Temp. (°C)	Rh (%)	SWR (W/m ²)	R ²	Warmest Aspect Orientation	South-Southeast Aspect Scaled Coef.	West-Southwest Aspect Scaled Coef.	Intercept β_a for Southeast Aspect	β_b Temp. Change	Temp. (Δ /1 cm)	Mean	Min	Max	Std Dev	Var
8/25/2018	12	21.8	75	80	0.60	W	0.26*	0.24*	30.62	0.72	1.14	31.81	31.08	32.56	0.254	0.064
7/29/2018	14	24.9	50	116	0.46	W	0.17**	0.19*	33.69	0.72	1.14	34.45	33.91	35.57	0.339	0.115
8/25/2018	13	24.8	66	85	0.57	W	0.28**	0.24**	33.78	0.69	1.10	34.93	34.37	36.09	0.332	0.111
8/24/2018	10	15.5	83	64	0.59	W	0.29*	0.18**	21.72	0.68	1.08	22.80	22.12	23.22	0.181	0.033
8/31/2018	11	19.6	65	83	0.58	W	0.21**	0.19**	28.77	0.68	1.08	29.88	29.29	31.14	0.375	0.141
8/27/2018	12	26.8	59	71	0.57	W	0.31*	0.28*	35.17	0.66	1.05	36.17	35.11	37.71	0.575	0.330
8/27/2018	10	22.7	79	63	0.61	W	0.22*	0.19*	28.87	0.65	1.03	29.73	29.10	30.37	0.216	0.047
8/26/2018	10	20.0	76	61	0.58	W	0.21**	0.20*	26.14	0.63	1.00	26.98	26.33	27.45	0.217	0.047
8/26/2018	11	22.1	68	79	0.59	W	0.31*	0.21**	30.26	0.62	0.98	31.15	30.51	32.24	0.368	0.135
8/25/2018	14	25.6	57	46	0.62	W	0.26*	0.17**	32.74	0.60	0.95	33.71	33.16	34.76	0.308	0.095
8/31/2018	10	16.9	75	53	0.57	W		0.13**	23.96	0.58	0.92	24.88	24.52	25.60	0.211	0.044
7/30/2018	14	26.1	46	121	0.51	W	0.20**	0.23*	34.65	0.58	0.92	35.56	34.93	36.83	0.394	0.155
7/30/2018	15	26.5	43	96	0.50	W	0.23**	0.21*	33.53	0.54	0.84	34.34	33.68	35.70	0.412	0.169
7/30/2018	13	24.6	53	114	0.50	W	0.21*	0.23*	33.42	0.53	0.84	34.25	33.69	35.42	0.357	0.128
8/25/2018	11	19.0	85	54	0.59	W	0.16**	0.16**	26.05	0.53	0.84	26.89	26.32	27.35	0.161	0.026
7/29/2018	15	25.6	46	103	0.52	W	0.19**	0.16*	33.50	0.52	0.83	34.26	33.84	35.41	0.350	0.123
8/6/2018	11	25.1	76	111	0.52	NW		0.19*	33.86	0.49	0.78	34.80	34.37	35.30	0.198	0.039

* $p < 0.001$; ** $p < 0.01$; *** $p < 0.05$; Temp. = temperature; Rh = relative humidity; SWR = shortwave reflectance; Coef. = coefficient; SE = standard error, Min = minimum; Max = maximum; Std Dev = standard deviation; Var = variance.

Table C-3. The TMP13 (SP) object correlations and parameter estimates between soil temperature derived by thermal infrared (IR), elevation, and aspect with statistical significance, including an hourly summary of environmental variables and soil temperature derived by thermal IR.

Date	Time	Environment Variables			Correlation and Parameter Estimates from Fit Model						Soil Temperature (°C)				
		Air Temp. (°C)	Rh (%)	SWR (W/m ²)	R ²	Warmest Aspect Orientation	East-Southeast Aspect Scaled Coef.	Intercept β_a for Southeast Aspect	β_b Temp. Change	Temp. (Δ /1 cm)	Mean	Min	Max	Std Dev	Var
8/7/2018	13	31.0	58	110	0.75	NE, E	-0.93*	47.24*	-3.32	-2.86	46.67	42.87	48.49	1.254	1.571
7/30/2018	15	26.5	43	96	0.79	NE, E, SE	-0.53*	37.33*	-3.16	-2.72	36.58	34.68	38.44	1.126	1.267
8/7/2018	12	29.7	61	113	0.74	NE, E	-0.96*	42.97*	-3.09	-2.66	42.49	39.07	44.41	1.193	1.422
8/25/2018	15	27.4	49	95	0.83	E	-0.68*	44.37*	-3.05	-2.63	43.75	41.04	45.17	1.084	1.174
8/7/2018	15	31.4	50	71	0.74	NE, E	-0.70*	44.90*	-2.63	-2.27	44.42	41.63	45.93	1.004	1.007
8/25/2018	13	24.8	66	85	0.79	E	0.69*	39.31*	-2.61	-2.25	38.84	36.40	40.04	0.958	0.918
8/26/2018	13	25.4	57	98	0.77	E	-0.58*	45.68*	-2.55	-2.20	45.17	42.59	46.34	0.941	0.885
8/24/2018	15	26.9	52	83	0.78	E	-0.65*	37.86*	-2.49	-2.15	37.38	35.79	39.08	0.919	0.845
8/26/2018	12	23.8	63	85	0.74	E	-0.61*	41.22*	-2.48	-2.14	40.75	37.99	41.81	0.938	0.880
8/27/2018	15	29.3	51	79	0.80	E	-0.47*	49.47*	-2.41	-2.08	48.93	46.63	50.11	0.865	0.748
8/27/2018	14	28.4	54	74	0.77	E	-0.51*	47.78*	-2.37	-2.04	47.28	45.02	48.36	0.873	0.762
8/25/2018	14	25.6	57	46	0.75	E	0.65*	38.87*	-2.34	-2.02	38.46	35.91	39.54	0.887	0.787
8/7/2018	14	30.8	59	53	0.70	NE, E	-0.71*	43.80*	-2.33	-2.01	43.43	40.59	44.73	0.923	0.852
8/27/2018	12	26.8	59	71	0.74	E	-0.55*	42.58*	-2.28	-1.97	42.14	39.68	43.12	0.865	0.748
8/27/2018	13	27.1	59	55	0.75	E	-0.51*	43.59*	-2.16	-1.86	43.17	40.85	44.15	0.811	0.657
8/26/2018	11	22.1	68	79	0.71	E	-0.54*	35.06*	-2.08	-1.79	34.69	32.43	35.69	0.810	0.657
8/26/2018	14	26.7	55	94	0.73	E	-0.45*	46.89*	-2.04	-1.76	46.46	44.45	47.40	0.769	0.592
8/25/2018	12	21.8	75	80	0.79	E	-0.39*	33.62*	-1.76	-1.52	33.25	31.80	34.19	0.639	0.409
8/27/2018	11	25.5	66	51	0.74	NE, E	-0.43*	35.77*	-1.70	-1.47	35.46	33.57	36.15	0.648	0.420
8/27/2018	10	22.7	79	63	0.70	NE, E	-0.37*	31.61*	-1.53	-1.32	31.32	29.69	32.07	0.598	0.358
8/26/2018	15	26.1	58	43	0.65	E	-0.38*	42.37*	-1.51	-1.30	42.09	40.33	42.83	0.610	0.372
8/6/2018	15	32.8	44	114	0.63	NE, E, SE	-0.25*	42.18*	-1.37	-1.18	41.87	40.89	43.08	0.548	0.300

Date	Time	Environment Variables			Correlation and Parameter Estimates from Fit Model						Soil Temperature (°C)				
		Air Temp. (°C)	Rh (%)	SWR (W/m ²)	R ²	Warmest Aspect Orientation	East-Southeast Aspect Scaled Coef.	Intercept β_a for Southeast Aspect	β_b Temp. Change	Temp. (Δ /1 cm)	Mean	Min	Max	Std Dev	Var
8/7/2018	11	28.3	66	106	0.64	E	-0.44*	37.28*	-1.36	-1.17	37.08	35.89	38.23	0.571	0.326
7/30/2018	14	26.1	46	121	0.62	NE, E, SE	-0.18***	37.32*	-1.35	-1.16	36.96	36.02	38.22	0.547	0.299
8/26/2018	10	20.0	76	61	0.69	E	-0.26*	28.04*	-1.28	-1.10	27.78	26.65	28.52	0.499	0.249
8/24/2018	14	26.1	51	91	0.60	NE, E, SE		36.98*	-0.98	-0.84	36.66	35.69	37.53	0.403	0.162
8/7/2018	10	26.2	75	82	0.70	NE, E	-0.22*	32.17*	-0.87	-0.75	32.01	31.41	32.71	0.340	0.116
8/31/2018	13	22.3	54	74	0.49	E, SE, S		38.67*	-0.77	-0.66	38.41	37.31	38.87	0.370	0.137
8/6/2018	12	28.4	65	119	0.70	Flat	-0.15*	39.05*	-0.77	-0.66	38.89	38.19	39.41	0.302	0.091
7/29/2018	11	23.2	57	110	0.77	NE, E, S, SW	-0.10*	32.26*	-0.72	-0.62	32.09	31.51	32.60	0.274	0.075
8/31/2018	12	21.5	56	81	0.52	S, SW		35.92*	-0.71	-0.61	35.64	34.56	36.20	0.369	0.136
8/6/2018	11	25.1	76	111	0.73	NE, E, S, SW	-0.11*	35.33*	-0.70	-0.60	35.17	34.59	35.59	0.267	0.071
7/29/2018	12	24.2	55	108	0.79	S, SW	-0.08**	34.79*	-0.70	-0.60	34.61	34.00	35.01	0.260	0.068
8/31/2018	15	23.0	53	60	0.42	E, SE		38.42*	-0.67	-0.58	38.20	37.15	38.75	0.337	0.114
8/6/2018	13	30.6	58	119	0.71	Flat		41.96*	-0.65	-0.56	41.78	41.13	42.22	0.255	0.065
7/29/2018	10	22.1	65	103	0.66	NE, E, S, SW	-0.12*	29.09*	-0.58	-0.50	28.98	28.40	29.40	0.238	0.057
7/29/2018	14	24.9	50	116	0.70	S, SW	0.06**	35.54*	-0.58	-0.50	35.31	34.64	35.66	0.246	0.060
7/30/2018	11	20.2	75	98	0.82		0.05**	29.19*	-0.56	-0.48	29.04	28.58	29.34	0.204	0.042
7/30/2018	13	24.6	53	114	0.73	S, SW		35.52*	-0.52	-0.45	35.35	34.77	35.66	0.208	0.043
8/31/2018	11	19.6	65	83	0.56	S, SE	0.17*	30.76*	-0.50	-0.43	30.51	29.72	31.20	0.311	0.096
8/24/2018	12	21.9	63	91	0.67		0.09*	33.40*	-0.50	-0.43	33.19	32.52	33.84	0.251	0.063

* $p < 0.001$; ** $p < 0.01$; *** $p < 0.05$; Temp. = temperature; Rh = relative humidity; SWR = shortwave reflectance; Coef. = coefficient; SE = standard error; Min = minimum; Max = maximum; Std Dev = standard deviation; Var = variance.

Table C-4. The TMP33 DP object correlations and parameter estimates between soil temperature derived by thermal infrared (IR), elevation, and aspect with statistical significance, including an hourly summary of environmental variables and derived soil temperature derived by thermal IR.

Date	Time	Environment Variables			Correlation and Parameter Estimates					Soil Temperature (°C)				
		Air Temp. (°C)	Rh (%)	SWR (W/m ²)	R ²	Warmest Aspect Orientation	Intercept β_a for Southeast Aspect	β_b Temp. Change	Temp. (Δ /1 cm)	Mean	Min	Max	Std Dev	Var
8/26/2018	12	23.8	63	85	0.27	E	35.61	-0.70	-1.46	35.34	34.45	36.14	0.386	0.149
8/25/2018	15	27.4	49	95	0.23	E	37.99	-0.66	-1.38	37.75	37.10	38.63	0.401	0.161
8/7/2018	11	28.3	66	106	0.32		36.34	-0.65	-1.35	35.91	35.63	36.32	0.147	0.022
8/26/2018	13	25.4	57	98	0.20	E	39.70	-0.65	-1.35	39.46	38.62	40.32	0.403	0.163
8/31/2018	11	19.6	65	83	0.31		30.44	-0.60	-1.25	30.20	29.68	30.71	0.258	0.066
7/29/2018	11	23.2	57	110	0.59		31.68	-0.55	-1.15	31.44	31.07	31.91	0.184	0.034
7/30/2018	13	24.6	53	114	0.57		34.39	-0.45	-0.94	34.23	33.94	34.65	0.141	0.020
7/29/2018	10	22.1	65	103	0.49	E	29.18	-0.45	-0.94	29.01	28.74	29.32	0.157	0.025
7/30/2018	11	20.2	75	98	0.65	SE, E	28.67	-0.39	-0.81	28.52	28.30	28.85	0.122	0.015
8/27/2018	11	25.5	66	51	0.38	E	31.75	-0.38	-0.79	31.61	31.30	31.98	0.165	0.027
8/6/2018	12	28.4	65	119	0.41		37.95	-0.36	-0.75	37.82	37.59	38.29	0.134	0.018
8/6/2018	14	32.0	52	115	0.35	SE, E	41.18	-0.34	-0.71	41.07	40.81	41.47	0.143	0.020
8/6/2018	11	25.1	76	111	0.37		34.58	-0.32	-0.67	34.48	34.22	34.84	0.121	0.015
7/30/2018	12	22.5	61	100	0.46	SE, E, S	31.01	-0.32	-0.67	30.90	30.67	31.17	0.114	0.013
7/29/2018	12	24.2	55	108	0.37		33.68	-0.31	-0.65	33.57	33.26	33.86	0.118	0.014
8/26/2018	11	22.1	68	79	0.37	SE, E, S	31.15	-0.30	-0.62	31.02	30.81	31.38	0.126	0.016
7/29/2018	14	24.9	50	116	0.36		34.48	-0.30	-0.62	34.40	34.11	34.76	0.125	0.016

* $p < 0.001$; ** $p < 0.01$; *** $p < 0.05$; Temp. = temperature; Rh = relative humidity; SWR = shortwave reflectance; Coef. = coefficient; SE = standard error, Min = minimum; Max = maximum; Std Dev = standard deviation; Var = variance.

Table C-5. The TMP19 SM object correlations and parameter estimates between soil temperature derived by thermal infrared (IR), elevation, and aspect with statistical significance, including an hourly summary of environmental variables and soil temperature derived by thermal IR.

Date	Time	Environment Variables			Correlation and Parameter Estimates						Soil Temperature (°C)				
		Air Temp. (°C)	Rh (%)	SWR (W/m ²)	R ²	Warmest Aspect Orientation	East-Southeast Aspect Scaled Coef.	Intercept, β_a for South Aspect	β_b Temp. Change	Temp. ($\Delta/1$ cm)	Mean	Min	Max	Std Dev	Var
8/26/2018	13	25.4	57	98	0.31	W, NW	0.96**	39.47	2.01	1.62	40.64	37.66	42.46	1.140	1.300
8/26/2018	12	23.8	63	85	0.32	W, NW	0.72**	35.87	1.97	1.59	37.09	35.04	38.73	1.000	0.999
8/27/2018	12	26.8	59	71	0.34	W, NW	0.63**	38.11	1.73	1.40	39.07	36.98	40.65	0.842	0.709
8/26/2018	11	22.1	68	79	0.40	W, NW		31.56	1.73	1.40	32.58	31.24	33.89	0.660	0.436
8/25/2018	15	27.4	49	95	0.25	W		37.48	1.38	1.11	38.28	37.05	40.83	0.690	0.476
8/27/2018	13	27.1	59	55	0.31	W, NW	0.61*	38.68	1.37	1.10	39.44	37.59	40.71	0.754	0.568
8/27/2018	10	22.7	79	63	0.39			29.83	1.36	1.10	30.62	29.76	32.04	0.456	0.208
8/7/2018	13	31.0	58	110	0.25	NW	0.81**	41.82	1.34	1.08	42.51	40.05	44.48	1.126	1.267
8/7/2018	12	29.7	61	113	0.21	NW		38.58	1.32	1.06	39.33	37.80	40.92	0.833	0.694
8/27/2018	14	28.4	54	74	0.26	NW	0.57**	42.39	1.24	1.00	43.06	41.23	44.43	0.785	0.616
8/27/2018	11	25.5	66	51	0.30	W	0.39*	32.83	1.16	0.94	33.53	32.26	34.56	0.577	0.333
8/26/2018	10	20.0	76	61	0.41	E		26.97	1.13	0.91	27.59	26.90	29.09	0.358	0.128
8/24/2018	12	21.9	63	91	0.35			32.25	1.08	0.87	32.80	32.20	34.85	0.385	0.149
8/26/2018	14	26.7	55	94	0.30	W, NW	0.75**	41.04	1.06	0.85	41.66	39.28	42.92	0.811	0.658
8/27/2018	15	29.3	51	79	0.24	NW		43.88	1.06	0.85	44.41	42.77	46.05	0.758	0.574
8/24/2018	11	19.2	69	81	0.37			28.12	1.01	0.81	28.68	28.03	30.50	0.335	0.112
8/24/2018	13	24.3	57	94	0.28			35.29	0.94	0.76	35.72	35.02	38.07	0.406	0.164
8/6/2018	11	25.1	76	111	0.37	NE		34.27	0.87	0.70	34.76	33.96	35.26	0.316	0.100
8/7/2018	15	31.4	50	71	0.23	W, NW	0.60**	39.72	0.86	0.69	40.17	38.43	41.49	0.739	0.547
8/7/2018	14	30.8	59	53	0.26	W, NW	0.65**	38.76	0.83	0.67	39.20	37.26	40.49	0.758	0.574
8/24/2018	10	15.5	83	64	0.44			22.75	0.80	0.65	23.22	22.77	24.37	0.241	0.058
7/29/2018	10	22.1	65	103	0.42	NE, E		28.63	0.78	0.63	29.12	28.63	29.68	0.252	0.063
8/25/2018	12	21.8	75	80	0.26			31.97	0.78	0.63	32.31	31.73	34.32	0.358	0.128

Date	Time	Environment Variables			Correlation and Parameter Estimates						Soil Temperature (°C)				
		Air Temp. (°C)	Rh (%)	SWR (W/m ²)	R^2	Warmest Aspect Orientation	East-Southeast Aspect Scaled Coef.	Intercept, β_a for South Aspect	β_b Temp. Change	Temp. ($\Delta/1$ cm)	Mean	Min	Max	Std Dev	Var
8/25/2018	14	25.6	57	46	0.21			33.60	0.76	0.61	34.01	33.30	35.50	0.354	0.125
8/26/2018	15	26.1	58	43	0.32	W, NW	0.59**	36.63	0.75	0.60	37.07	35.44	38.05	0.592	0.350
8/7/2018	11	28.3	66	106	0.34	E		35.61	0.67	0.54	35.97	35.42	36.46	0.247	0.061
8/25/2018	11	19.0	85	54	0.32			26.86	0.66	0.53	27.21	26.86	28.58	0.237	0.056
8/6/2018	10	21.6	90	95	0.33	NE		29.59	0.64	0.52	29.96	29.37	30.37	0.232	0.054
8/6/2018	12	28.4	65	119	0.28	NE		37.81	0.64	0.52	38.11	37.23	38.49	0.299	0.090
7/29/2018	11	23.2	57	110	0.32	NE		31.27	0.63	0.51	31.64	31.14	32.13	0.250	0.063
8/20/2018	12	22.1	69	89	0.31			33.57	0.60	0.48	33.90	33.43	34.47	0.221	0.049
7/29/2018	12	24.2	55	108	0.31	NE, E		33.49	0.59	0.48	33.83	33.41	34.22	0.237	0.056

* $p < 0.001$; ** $p < 0.01$; *** $p < 0.05$; Temp. = temperature; Rh = relative humidity; SWR = shortwave reflectance; Coef. = coefficient; SE = standard error, Min = minimum; Max = maximum; Std Dev = standard deviation; Var = variance.

Table C-6. The TMP11 DM object correlations and parameter estimates between soil temperature derived by thermal infrared (IR), elevation, and aspect with statistical significance, including an hourly summary of environmental variables and soil temperature derived by thermal IR.

Date	Time	Environment Variables			Correlation and Parameter Estimates						Soil Temperature (°C)				
		Air Temp. (°C)	Rh (%)	SWR (W/m ²)	R ²	Warmest Aspect Orientation	Direction Effects	Intercept β_a for South Aspect	β_b Temp. Change	Temp. (Δ /1 cm)	Mean	Min	Max	Std Dev	Var
8/31/2018	15	23.0	53	60	0.55	W	0.34*	32.62	1.03	1.16	35.93	34.92	36.89	0.544	0.296
8/31/2018	14	22.2	55	44	0.53	W	0.24*	30.57	0.93	1.04	33.67	32.71	34.52	0.509	0.260
8/31/2018	12	21.5	56	81	0.55	W	0.32**, 0.30**	31.05	0.92	1.03	34.25	32.97	35.58	0.719	0.517
8/31/2018	13	22.3	54	74	0.53	W	0.32*, 0.23**	32.66	0.91	1.02	36.14	35.10	37.30	0.619	0.383
8/31/2018	11	19.6	65	83	0.60	W	0.19**, 0.21**	28.77	0.68	0.76	30.37	29.77	31.37	0.427	0.182
8/31/2018	10	16.9	75	53	0.57	W	0.13**	23.96	0.58	0.65	24.63	24.35	24.96	0.105	0.011

* $p < 0.001$; ** $p < 0.01$; *** $p < 0.05$; Temp. = temperature; Rh = relative humidity; SWR = shortwave reflectance; Coef. = coefficient; SE = standard error, Min = minimum; Max = maximum; Std Dev = standard deviation; Var = variance.

Abbreviations

AI	Artificial intelligence
AITD/R	Automatic target detection and recognition
ANOVA	Analysis of variance
ATR	Automatic target recognition
AUC	Area under the curve
bgs	Below ground surface
C5ISR	Command, Control, Communications, Computers, Cyber, Intelligence, Surveillance, and Reconnaissance
CRREL	US Army Cold Regions Research and Engineering Laboratory
CNN	Convolutional neural network
CV	Computer vision
DM	Deep metal
DP	Deep plastic
DWT	Discrete wavelet transformation
ERDC	Engineer Research and Development Center
ESE	East-southeast
FAR	False alarm rate
FLIR	Forward-looking infrared
GPR	Ground-penetrating radar
GSL	US Army Geotechnical Structures Laboratory
iid	Independent and identically distributed
IR	Infrared

I16	16-bit signed
LWIR	Long-wave infrared
MAE	Mean absolute error
ML	Machine learning
MSE	Mean square error
NMSE	Normalized mean square error
PCA	Principal component analysis
R-CNN	Region-based convolutional neural network
Rh	Relative humidity
RMS	Root-mean-square
RMSE	Root mean square error
ROC	Receiver operating characteristic
ROI	Region of interest
RSS	Root sum of squares
SE	Standard error
SM	Shallow metal
SNR	Signal-to-noise ratio
SP	Shallow plastic
SWR	Shortwave reflectance
TCRNet	Target-to-clutter-ratio neighborhood enrichment test
U8	8-bit unsigned
WSW	West-southwest
YPG	Yuma Proving Ground

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